Rowing Performance Analysis Using Motion Sensors

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presented by
Franz Gravenhorst

Dipl.-Ing., University of Karlsruhe, Germany
born on September 24th, 1985
citizen of Germany

accepted on the recommendation of
Prof. Dr. Gerhard Tröster, examiner
Prof. Dr. Richard Smith, co-examiner

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Contents

Abstract .................................................................................................................... xiii
Zusammenfassung .................................................................................................... xv

Chapter 1 Introduction ............................................................................................ 1
  1.1 Rowing Basics ............................................................................................... 2
  1.2 Performance Analysis in Rowing ................................................................. 4
    1.2.1 Sensors in Rowing .................................................................................. 4
    1.2.2 Performance Influence Factors ............................................................. 6
    1.2.3 Individual Rowing Performance ............................................................. 8
    1.2.4 Crew Technique ................................................................................... 10
    1.2.5 Material Optimization ......................................................................... 11
  1.3 Objectives of the Thesis ................................................................................. 12
    1.3.1 Designing Components for Instrumenting Rowing Boats ...................... 13
    1.3.2 Performance Analysis using Rowing Sensor Data .................................. 14
    1.3.3 Data-Driven Identification of Rowing Fingerprints ............................... 14
  1.4 Thesis Outline ............................................................................................... 14
  1.5 Additional Publications .................................................................................. 16
    1.5.1 Additional Rowing-Related Publications ........................................... 17
    1.5.2 Gait Analysis for Runners ..................................................................... 17
    1.5.3 Publications on Pervasive Healthcare .................................................. 17
    1.5.4 Group Behavior Analysis ..................................................................... 19
Contents

1.5.5 Multimodal Hearing Instruments ...........................................19
1.5.6 Invited Talks ........................................................................20

Chapter 2  Thesis Summary .................................................................21
2.1 Designing Components for Instrumenting Rowing Boats ............22
  2.1.1 IMU-based system for sensing oar movements ................22
  2.1.2 IMU module attached to oar ...........................................23
  2.1.3 IMU module inside oar ..................................................25
  2.1.4 Smartphone on oar: “Strap and Row” ............................26
  2.1.5 Seat position tracker based on IMUs ......................29
  2.1.6 Seat position tracker based on UltraSonic ....................31
  2.1.7 Boat movement analysis with gyroscopes ....................33
2.2 Performance Analysis using Rowing Sensor Data  .....................34
  2.2.1 Case studies based on oar measurements ....................34
  2.2.2 Stroke classification based on sliding seat movement 37
2.3 Data-Driven Identification of Rowing Fingerprints ....................39
2.4 Conclusion ............................................................................44
2.5 Outlook ....................................................................................45

Chapter 3  Strap and Row: Rowing Technique Analysis with Mobile Phones ....................................................................47
3.1 Introduction ............................................................................48
  3.1.1 Motivation ....................................................................48
  3.1.2 Rowing Basics ..............................................................49
  3.1.3 State of the Art ..............................................................50
  3.1.4 Contribution ....................................................................51
7.4.2 Results and Discussion ............................................... 118
7.5 Conclusion and Outlook ........................................................ 122

Chapter 8 SonicSeat: Seat Position Tracker based on Ultrasonic Sound Measurements ........................................................................... 125

8.1 Introduction .......................................................................... 126
  8.1.1 Rowing Technique ...................................................... 127
  8.1.2 Previous Work .................................................................. 128
  8.1.3 Related Work .................................................................. 128
  8.1.4 Contributions ............................................................. 129

8.2 Seat Position Tracking System ............................................... 130
  8.2.1 Requirements ............................................................. 130
  8.2.2 Seat Tracking based on Ultrasonic Sound .................. 131

8.3 Training Analysis .................................................................... 133
  8.3.1 Performance Metrics ................................................. 133
  8.3.2 Data Analysis .............................................................. 139

8.4 Evaluation Experiment .......................................................... 140
  8.4.1 Indoor Rowing Simulator Setup .................................. 140
  8.4.2 Measurement Results ................................................ 141

8.5 Application on the Water ...................................................... 143

8.6 Limitations ............................................................................. 146

8.7 Conclusion and Outlook ........................................................ 147

Chapter 9 Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed ......................................................................... 149

9.1 Introduction .......................................................................... 150
9.1.1 Motivation .................................................................150
9.1.2 Rowing Basics.............................................................152
9.1.3 Related Work .............................................................155
9.1.4 Contribution ...............................................................157
9.1.5 Paper Organization ....................................................158
9.2 Performance Metrics for Individual Rowers and Crews........158
  9.2.1 Performance Metrics for all Boat Types ....................159
  9.2.2 Additional Performance Metrics for Crew Boats: Synchronicity Measures .............................................161
9.3 Experiment Setup ..................................................................162
  9.3.1 Mobile On-Boat Measurement System .....................162
  9.3.2 Test Races for Data Collection ...................................163
  9.3.3 Feature Calculation ....................................................163
9.4 Methods ................................................................................165
  9.4.1 Biomechanical Fingerprint Identification: Wrapper-Based Feature Selection .............................................166
  9.4.2 Correlations with Boat Speed: Linear Regression Analysis ..........................................................170
9.5 Results ...................................................................................173
  9.5.1 Biomechanical Fingerprint Identification...................173
  9.5.2 Correlations with Boat Speed: Linear Regression Analysis ..........................................................175
9.6 Analysis and Discussion .........................................................177
  9.6.1 Biomechanical Fingerprint Identification...................177
  9.6.2 Correlations with Boat Speed ....................................181
<table>
<thead>
<tr>
<th>Chapter</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.7</td>
<td>Limitations</td>
<td>183</td>
</tr>
<tr>
<td>9.8</td>
<td>Conclusion</td>
<td>184</td>
</tr>
<tr>
<td>9.9</td>
<td>Outlook</td>
<td>185</td>
</tr>
<tr>
<td>9.10</td>
<td>Appendix</td>
<td>187</td>
</tr>
</tbody>
</table>

References ................................................................. 191

Glossary ................................................................. 203

Curriculum Vitae ...................................................... 205
Abstract

Rowing uses the whole body in a complex set of movements, which in crew boats should be synchronised. Currently, however, it is difficult to objectively analyse rowers’ technique and crew compatibility. This limits coaches’ and athletes’ capacity to improve boat speed and to prevent injuries. In this work we investigate the application of motion sensors for rowing performance analysis. The three main objectives are 1) designing and implementing novel sensing approaches in rowing, 2) introducing algorithms to translate raw sensor data into rowing performance metrics and 3) applying machine learning methods to identify the most discriminant metrics.

In contrast to the state-of-the-art we focus on unobtrusive technology which means the sensors can be integrated into rowing equipment or installed without expert knowledge and do not obstruct the rower. This approach has the potential to make rowing performance analysis accessible as a coaching tool for all levels of competitive rowing.

We introduce and evaluate three different implementations for measuring the horizontal oar angle based on inertial measurement units (IMU). To compute the oar angles from the raw sensor measurements we present four different rowing-specific modifications of the state-of-the-art strap-down algorithm. An IMU sensor implemented into the rowing oar enables the measurement of the stroke length with an error of 1.56° ± 0.63°. Smartphones with integrated IMU sensors strapped around the oar deliver an error of 7.64° ± 2.95°.

In order to measure the seat position we present two contactless sensor setups based on acceleration and ultrasonic sound sensors. The latter system obtains the seat displacement with an error of 1.13% ± 0.75%. In an on-water experiment typical rowing mistakes such as “rushing the slide” can be detected and match the evaluation of a human coach.
Abstract

Rowing crews aim for the most stable and smooth boat movements possible. To compare the influence of the boat type on the boat stability we suggest a sensor setup with a miniaturized gyroscope sensor. We demonstrate the system by measuring two different boats rowed by the same crew. The average amplitude of the vertical angular velocity of boat B was 60% higher than boat A.

An increasing number of sensors in rowing and measured data ask for efficient ways of selecting the most relevant metrics for specific use cases. We introduce a data-driven approach to identify the biomechanical fingerprint of a rower. These metrics summarize the most discriminative features of each rower within a group of athletes. In collaboration with Olympic-level national teams we exhibit how our approach can support coaches in selecting the best-fitting crew. In an experiment we selected the two best-fitting athletes to make up a double scull from a group of four female rowers. We identified the “Finish Slip” and the “Angular Drive Acceleration Point” as the most discriminant features for this group. We picked the two rowers who had the most similar values considering these two most discriminant features. The 2000m race time of all possible crew combinations was measured and the two picked rowers proved to be the fastest of all tested combinations and later scored an Olympic medal.

This thesis presents how advances in sensor technology combined with domain-specific signal processing and machine learning algorithms can support athletes and coaches in analysing rowing performance.


Es werden drei verschiedene Methoden vorgestellt und evaluiert, um den horizontalen Ruderwinkel mit Inertial-Sensoren (inertial measurement units, IMUs) zu messen. Für die Berechnung der Ruderwinkel werden vier Varianten von „Strap-Down“ Algorithmen beschrieben, die speziell für Ruderbewegungen angepasst wurden. Mit dem System, bei dem der IMU-Sensor in den Ruderholm integriert wurde, kann die Länge des Ruderschlages mit einem Fehler von 1.56°±0.63° gemessen werden. In einer anderen Variante wurde ein Smartphone als Sensor verwendet, indem es auf den Innenhebel
Zusammenfassung

des Ruders befestigt wurde. Der Fehler dieses Messsystem beträgt 7.64° ± 2.95°.

Um die Bewegung des Rollsitzes im Ruderboot zu messen, werden zwei kontaktlose Messmethoden vorgestellt, basierend auf Beschleunigungs- und Ultraschallsensoren. Das Ultraschall-System misst die Rollsitzposition mit einem Fehler von 1.13% ±0.75%. In einem Experiment auf dem Wasser können typische Ruderfehler, wie beispielsweise zu schnelles Vorrollen, erkannt werden.

Ruderboote sollten möglichst stabil und gleichmäßig durch das Wasser gleiten. Um Bootsstabilität von verschiedenen Ruderbooten zu vergleichen, wird ein Drehraten-Sensor im Boot befestigt. Exemplarisch werden zwei Boote mit jeweils der selben Mannschaft gerudert und die Messergebnisse verglichen. Im Ergebnis weist Boot B eine um 60% größere durchschnittliche Amplitude der vertikalen Winkelgeschwindigkeit auf als Boot A.


Diese Arbeit zeigt auf, wie neue Sensortecnologien mit entsprechender Signalverarbeitung und datengetriebenen Auswertungsmethoden dazu benutzt werden können, um Sportler und Trainer in der Analyse von Ruderbewegungen zu unterstützen.
Chapter 1  Introduction

This chapter explains the basic rowing movement and key factors that influence rowing performance. It then reviews the state-of-the-art in sensing and post-processing systems for the evaluation of boats’ and rowers’ movements. Finally, the objectives of this thesis are summarized and the structure for the following chapters is laid out.
1.1 Rowing Basics

Rowing is one of the oldest Olympic disciplines and is very popular amongst both spectators and athletes. Between 2004 and 2008 the number of participating athletes grew by 5% annually in the United States, totalling to 220,000 rowers in 2008 [12, 14], and it is expected to keep following this trend in the years ahead. The fastest growing numbers are the high school and master rowers.

The goal in rowing is to move the boat as fast as possible from start to finish, usually over the Olympic distance of 2000m. The boat travels backwards, meaning the rower’s back faces the direction of movement. The rower sits on a sliding seat allowing the body to move forwards and backwards, enabling the rower to further extend the stroke length. The rowing movement is cyclic and consists of two phases, the drive phase and the recovery phase. There are two sub-types of rowing: sweep-oar, in which each rower holds one oar and rotates either to the left or right side; and sculling, in which each rower holds two oars making symmetric movements with the left and right oar. For the sake of simplicity the further descriptions focus on sculling, however most movements are similar in sweep rowing.

**Rowing Stroke.** Figure 1 depicts two male scullers during different phases of their rowing stroke. The drive phase starts in the forward most position, called the catch position (Figure 1a). The legs are bent, so that the shins are perpendicular to the water, the sliding seat is as close to the stern of the boat as possible, the upper body and shoulders are in front of the hips, and the arms and hands are fully extended, reaching out for maximal length. The blades are then placed into the water (Figure 1b). They are then driven through the water by pushing the oars against the pins. This force is generated by pushing back with the legs, moving the seat towards the bow, bending the arms and taking the upper body back so that the shoulders are just behind the hips, while the back remains relatively straight. When the net force of the oars pushing against the pins exceeds the drag of the water on the boat it will accelerate towards the finish line.
At the back most position, called the finish position (Figure 1c), the blades are extracted from the water and the recovery phase begins. During this phase, the rower prepares for the next stroke, moving the blade above the water to the catch position again. To minimize air drag and to increase boat stability, the blade is turned and moved into a feathered position above the water (Figure 1d). Finally, the blade has to be turned again so that it is at a right angle to the water, this is known as a squared blade. The cycle then starts again with the next drive phase (Figure 1a). The swept angle between the start and the end of the stroke is called stroke length.

Figure 1: Different phases of a basic rowing stroke, performed in a men’s double scull. The boat is moved backwards (from left to right). At the catch position (a) the blades are placed into the water. At position (b) the boat is accelerated by pushing back with the legs and bending the arms until the rower reaches the finish position (c). The blades are extracted from the water and feathered (turned parallel to the water). Then the rower reaches forward, bending their legs and extending the arms (d) to prepare for the next catch position (a). Then the cyclic movement continues with the next stroke. [41]

This stroke is repeated over and over again. A standard base training rate is 18-20 strokes per minute, while in 2km races it is generally between 32-37 strokes per minute. During the start, finish sprint and other strategic points in a race, the stroke rate can reach up to 43 strokes per minute.

Making the boat fast. The more force a rower applies the faster the boat is accelerated. However, muscle mass increases a rower’s weight, and the heavier a boat is the greater the drag factor. Therefore, the potential gain of boat speed through strength is limited and this is where rowing tech-
nique becomes essential. By improving the technique the rower can manage to increase the boat speed with constant strength (and body mass) [35]. As a fluctuating boat velocity is inefficient, the rower attempts to minimise both positive and negative accelerations. Deceleration of the boat occurs mainly due to the forces applied to the footstretcher as the rower comes towards the catch. Deceleration is also caused by unstable boat movements, unsmooth oar movements and delays in placing the blade at the catch position.

Crew Boats. In crew boats the individual rowers’ techniques have to fit with the other crew members. According to Soper et al. this “ideal fitting” includes several aspects, for example similar force profile characteristics have a significant influence on the success of a crew sculling boat [98]. Many coaches share the assumption that rowers in crew boats should move as synchronously to each other as possible. For the case of sculling, this is supported by many studies [27, 53, 109]. However, for sweep rowing some authors argue that slightly opposite styles could also complement each other in a positive way [93].

1.2 Performance Analysis in Rowing

1.2.1 Sensors in Rowing

There are qualitative rowing technique guidelines from national and international rowing associations which explain basics of good rowing technique [35, 15, 37]. Key aspects include stroke efficiency, rhythm, timing, and boat stability. There are quantitative (e.g. velocity, stroke count) and qualitative (e.g. smoothness of movement) measures, but there is a strong need for both rowers and coaches to have more quantitative measures [102]. This has been an active field in research for a long time, rowing technique and performance analysis using electronic evaluation has been pursued by science for more than 30 years. One of the first approaches was carried out in 1980 by Schneider [86], who used telemetry and post-recording evaluation. Gyroscope sensors were first used in [105]. They were attached to the
boat in order to analyse boat stability. Due to the weight and form factor of the early versions of these sensors, it was not feasible to attach them to rowing oars. Various research has been carried out to analyse rowing motions in dry setups, like rowing on ergometers [19, 58, 17] or on rowing simulators [103, 80].

Thanks to its miniaturization, more and more sensor devices can now also be fitted into rowing equipment and more measurements can be carried out in on-water setups. The most common electronic device used in rowing boats is the StrokeCoach device by NielsenKellermann [74]. The purpose of the StrokeCoach is to measure the stroke rate by detecting the seat sliding intervals. However, this system does not provide further information concerning the continuous trajectory of the seat movement. Kleshnev [63] and Smith [96] presented a method to measure the seat position using a cord which connects the sliding seat to a potentiometer. This system delivers reliable measurements but also interferes directly with the rower as the attached cord constantly pulls the seat backward. Davoodi presented a system to track the seat position by optical methods [33]. This system works well for indoor rowing. However, it has not yet been tested for on-water environments.

Schaffert et al. [85] equipped a boat with accelerometers and converted the sensor measurements into sound, which was then played back to the athlete in real-time. Sinclair et al. [92] presented a setup for measuring the force applied to a rowing oar. The most common approach to measure the
horizontal oar angle is based on wired potentiometers [71, 63]. Sabatino et al [83] describe a feedback measurement system, in which a piezoelectric gyro is used. It consists of two Palm handhelds, one in the boat and one for the coach. Bonnet et al [25] focus on decreasing the drift problems of gyros for runners using a weighted Fourier linear combiner filter to create an estimation of the 3D orientation. Kleshnev [60, 62] and Smith et al [95] worked on the kinematics of rowing to classify what a good rowing stroke is. Nolte’s research finds optimal stroke lengths according to different shapes of the oar [75]. He achieves this by focusing on acceleration and oar angles, which are measured with potentiometers. Several feedback methods and the suitable data processing approaches are discussed and compared to the traditional rower/coach feedback in [61]. An additional approach for classifying stroke lengths is described in [58], where body sensor gyros placed at the femur and lower back record the moves of the rowing stroke. Another research group also focused on stroke length measurement with IMUs [68] by implementing the system 'Remote', which is compared to a commercial measurement system. The results promise a high potential of IMU measurement systems for movement analysis in rowing. The idea of using mobile inertial measurement units for rowing technique analysis is already patented [5] but there is still no extensive product commercially available.

1.2.2 Performance Influence Factors

The overall performance in rowing races is measured as the time interval a boat needs to travel from the start to finish of a race. This overall performance depends on a number of influence factors [31, 52, 57, 64, 69, 96, 94], the most relevant ones are depicted in Figure 3.

Influences from the environment, such as wind, water conditions or temperature directly impact boat stability and water and air friction. Results show that experienced Olympic level crews, who race several times in the same boat under changing environmental conditions, achieve finish times that vary by more than 10 seconds [9] whereas the first three ranks within a race are usually separated by only fractions of a second.
Race strategy is another variable in rowing races; it describes the distribution of sprints during a race and how a crew reacts to specific race situations.

There is a broad market for racing boats, oars and rowing accessories. There are different models and each model offers dozens of options for customization, for example the foot stretcher or rigger position and the oar length. Rowers have to decide on the material and the settings they want to use to enable maximum performance.

Rowers’ individual capabilities have a significant impact on their performance. These capabilities are based both on physical strength and technique. The ideal rowing technique is both efficient and avoids injuries [15],
enabling the rower to achieve best performances with the least possible effort in a sustainable way.

A successful **crew** requires not only individually competent rowers, but rowers whose technique fits well together. Consequently, a trade-off between best individual technique and crew synchronization often has to be found.

In this work, the influence of the environment on performance is not considered because in common on-water race setups the environment cannot be controlled or manipulated. Similarly, the influence of race strategy is not considered in detail here because theories regarding optimal race strategies are already well established [39]. The next three sub-chapters provide an overview of the state of the art for the remaining three influence factors, including individual performance, crew technique and material.

### 1.2.3 Individual Rowing Performance

To perform at the top level elite rowers must be both physically strong and have excellent technique. Good rowing technique is not only important for speed, but should be practiced by rowers at all levels to minimize the risk of injury. To monitor and improve their technique elite and non-elite rowers alike usually rely on human coaches who accompany training sessions and give feedback. Coaches obtain support from traditional tools such as stopwatches and high-speed video cameras, as well as a growing number of sensor-based approaches. The general developments in this research area are described in chapter 1.2.1, and a more extensive overview of sensors for instrumented rowing boats and analysis is presented in Table 1 and in the following paragraphs.

Through these sensing approaches a broad range of modalities can be recorded. Finding methods to automatically analyse the acquired data and provide appropriate feedback for the coaches and athletes are active research fields in the biomechanics and sports technology community [20, 46, 96, 102].
<table>
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<tr>
<th>Sensor</th>
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<th>Description</th>
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<tr>
<td>Magnet</td>
<td>Seat</td>
<td>Reed switch to count strokes [74]</td>
</tr>
<tr>
<td>Impeller</td>
<td>Boat</td>
<td>Measure distance and speed relative to the water [74]</td>
</tr>
<tr>
<td>GPS</td>
<td>Boat</td>
<td>Measure distance and speed relative to the shore [74]</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Boat</td>
<td>Measure stroke rate and interpolate boat movement [50]</td>
</tr>
<tr>
<td>Gyroscope</td>
<td>Oars</td>
<td>Measure oar angles [83]</td>
</tr>
<tr>
<td></td>
<td>Boat</td>
<td>Measure boat stability [44, 105]</td>
</tr>
<tr>
<td>Potentiometer</td>
<td>Oarlock</td>
<td>Measure horizontal oar angle [37]</td>
</tr>
<tr>
<td>Force sensor</td>
<td>Oarlocks</td>
<td>Measure force applied to oars [92]</td>
</tr>
<tr>
<td></td>
<td>Foot stretcher</td>
<td>Measure force applied on the foot stretcher [96]</td>
</tr>
<tr>
<td>Strain gauge</td>
<td>Oars</td>
<td>Measure bending force of oars [76]</td>
</tr>
<tr>
<td>Inertial measurement units</td>
<td>Oars, boat</td>
<td>Measure oar and boat orientations and movements [42, 102]</td>
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<td>(accelerometer, gyro, compass)</td>
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Table 1: Sensors used for rowing in on-water setups, adapted from [102, 41]

Millward developed a model considering the fluid mechanics of the oar and verified it with rowing performance data [72]. He identified the shape of the rowing force curve and the proportion of recovery time in the total stroke as important factors for the boat speed. Sanderson and Martindale developed an equation to describe the boat speed as a function of the movement of the rower's centre of mass and the applied force [84]. To increase the efficiency, the authors suggested building lighter boats, increasing the blade area of the rowing oar and finding an ideal stroke rate depending on the rower’s body mass.
Medical and physiological determinants for boat speed are explored in numerous clinical studies. Baguet et al. found that specific nutrition and supplements have a significant impact on the physiological system and increase the performance of elite rowers. After a 7-week study his treatment group improved an average of 4.3 seconds more than the placebo group [22]. Ingham et al. measured the oxygen intake during ergometer rowing. The best correlation to the resulting 2000m performance was the applied power during maximum oxygen consumption [54].

Secher and Vaage presented a mathematical model for forecasting the racing times of male and female rowers depending on body mass. They found that heavyweight rowers had a 2.6% advantage in comparison to lightweight rowers. This value was supported by on-water results [87].

1.2.4 Crew Technique

**Individual performance and synchronization.** In the Olympic regatta rowers compete not only in singles but also in crew boats of up to eight rowers. Results show that crews made up of the best single scullers are often beaten by crews made up of rowers with worse individual performances. As Daniel Topolski, one of the most successful coaches of the annual Oxford-Cambridge boat race stated, “[t]he sum of a crew is greater than its parts” [82]. This has become a well-established saying and highlights that making a crew boat successful requires more than a group of individually fast rowers.

Different athletes often have different ideal single sculling technique as they have different skill levels, body proportions and anatomy [15]. As such, athletes who perform at the top level are likely to have slightly different technique from one another [28, 29, 95, 102]. Rowers in crew boats must be able to synchronize their technique and timing with each other in order to achieve top results [27, 53, 109]. However, as Korndle et al. show, in practice rowers only manage to adapt some aspects of their technique to match the crew. Regardless of the crew or boat class rowers are put in, they usually maintain their individual “signature” force angle profile, [65].
Introduction

Through a more systematic analysis of a group of female rowers Galloway et al. were able to support this finding [38].

**Crew selection.** The most common approach for finding ideal rowing crews within a pool of athletes is through test races. Coaches put crews together and organize races to determine which crew in which seating order performs best. It is usually not practical to test all possible combinations due to time restrictions and the difficulty of ensuring comparable conditions between so many test races.

To decide which of the possible crew combinations are selected to perform test races against each other, coaches currently generally rely on their subjective evaluations and personal experience. This process lacks objective, checkable and reproducible reasoning and often leaves the non-selected athletes with unanswered questions and a feeling that they were potentially unfairly overlooked.

Galloway et al. suggest that biomechanical parameters such as force profiles can be used to evaluate the compatibility of individual athletes to form a crew [38]. There are many possible metrics that could be extracted and some are already measured in leading high-performance rowing centres. Identifying which biomechanical parameters are most suited for determining which athletes fit best together is an active research field.

1.2.5 Material Optimization

**Material availability.** The regulations for international rowing events, laid out in the FISA Rules of Racing [35], state that the “construction, design and dimensions of boats and oars shall, in principle, be unrestricted [...]” (Rule 33). This contributes to a market offering a broad variety of rowing boats that allow for the adjustment of a number of mechanical settings such as the position of the oarlock and the foot stretcher. The ideal boat and settings depend on individual characteristics of a given crew, such as anatomy or rowing style. To the best of our knowledge, there is no standardized test procedure available which allows for the evaluation and optimization of rowing boats and its settings [37].
**Boat comparison.** In order to decide which brand and type of boat to use most coaches rely on their own subjective feelings or on subjective feedback from crew members [37]. Common technical tools used to aid in the decision process include high-speed cameras and stopwatches. While cameras enable coaches to have a close look at the boat’s movement, this method only allows qualitative analysis and conclusions depend on the coach’s experience. Stopwatches can be used to compare the overall time a given crew achieves for a given race distance in different boats. However, it is difficult to ensure the comparability of this approach as it relies on the repeatability of the test race conditions, which includes the crews’ physical, psychological and technical strength, the same water surface and current conditions, as well as the same wind and temperature.

![Figure 4: Boat instability contributes to loss of energy. Possible angular turning directions: a) Roll b) Yaw c) Pitch. [44]](image)

According to [15, 37] the stability and straightness of the boat movement is crucial for the boat’s performance. Any variations to the boat’s expected main moving direction leads to increasing drag forces and a loss of energy [92]. The possible three turning directions are illustrated in Figure 4.

### 1.3 Objectives of the Thesis

The overall goal of the thesis is the exploration of different sensing and post-processing methods for performance analysis in competitive rowing. Proposed systems should be usable in real-life training situations, obey official regulations and be accurate enough to offer beneficial insights for the training process.
Specifically, the topics which are described in the following three sub-chapters will be investigated in this thesis.

1.3.1 Designing Components for Instrumenting Rowing Boats

To carry out rowing performance analysis we first have to acquire measurements that describe the rowing movements. In order to obtain such measurements, we focused on developing and optimizing sensors, their position placements and post-processing algorithms. We asked:

- With which sensors and at which sensing locations can we obtain movement data in an unobtrusive way, meaning that the sensors do not interfere with or obstruct the rower?
- How accurately can we measure oar movements with miniaturized IMUs which are a) attached on the oar or b) implanted in the oar?
- Can we obtain oar angle measurements when exploiting c) smartphones as sensing devices, which include (low-grade) IMU modules?
- What are the advantages and disadvantages of each proposed oar measurement system a)-c)?
- For all proposed sensing systems a)-c): How can we adjust the state-of-the-art algorithms to improve the accuracy of the computation of the horizontal oar angle from the raw sensor measurements?
- How can we continuously track the seat position by using d) acceleration or e) ultrasonic sound sensors?
- How can we optimize the post-processing algorithms for d) to deal with sensor drift and misalignments?
- How can we measure the stability of rowing boats to identify the most stable boat for a given crew?
1.3.2 Performance Analysis using Rowing Sensor Data

Based on the proposed components (see 1.3.1) for instrumented rowing boats, we investigate how the obtained data of specific modalities can be used for performance analysis. The goal is to deliver data that supports coaches to improve rowers’ individual rowing technique.

- Which performance metrics can be calculated from raw sensor data?
- How can calculated and visualized features support coaching or material selection decisions?

1.3.3 Data-Driven Identification of Rowing Fingerprints

A crew boat consists of two to eight rowers and each one can move individually. This results in a high dimensionality of obtainable movement data. We investigate a data-driven approach how differences in rowing technique for elite athletes can be identified within a high-dimensional dataset. The resulting selection of rowing metrics is unique for each individual athlete and most discriminant within a group of athletes. This “biomechanical fingerprint” can be applied in a use-case to find the combination of athletes that fit together best for a crew boat. This objective can be formulated in two research questions:

- How can we identify the most discriminative features for a group of rowers?
- How can the measured data be condensed and support in making crew selection decisions?

1.4 Thesis Outline

This thesis includes seven publications [42, 49, 47, 44, 102, 46, 41] which address the objectives which were introduced in the previous sub-chapter. Figure 5 briefly illustrates how each publication contributes to the objec-
tives and in which chapter they can be found. Full details of the publications are listed in Table 2.

Figure 5: Thesis outline, contributions grouped by objectives

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Publication</th>
</tr>
</thead>
<tbody>
<tr>
<td>– System Design –</td>
<td></td>
</tr>
</tbody>
</table>
| 3 | Strap and Row: Rowing Technique Analysis Based on Inertial Measurement Units Implemented in Mobile Phones  
Franz Gravenhorst, Amir Muaremi, Felix Kottmann, Roland Sigrist, Nicolas Gerig, Conny Draper and Gerhard Tröster  
*In: Proceedings of International Conference Series on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP 2014)* |
| 4 | Validation of a Rowing Oar Angle Measurement System based on an Inertial Measurement Unit  
Franz Gravenhorst, Timothy Turner, Conny Draper, Richard M. Smith and Gerhard Tröster  
in: *Proceedings of the 12th IEEE International Conference on Ubiquitous Computing and Communications (IUCC-2013) [Best Student Paper Award], Melbourne, Australia, 2013* |
| 5 | Self-Aligning and Drift-Compensated Rowing Seat Position Measurement System Based on Accelerometers and Magnetometers  
Franz Gravenhorst, Christoph Thiem, Bernd Tessendorf, Rolf Adelsberger, Christina Strohrmann, Bert Arnrich and Gerhard Tröster  
Introduction

| 6 | Analyzing Rowing Crews in Different Rowing Boats based on Angular Velocity Measurements with Gyroscopes  
Franz Gravenhorst, Bernd Tessendorf, Bert Arnrich, Camille Codoni and Gerhard Tröster  
in: *Proceedings of the International Symposium on Computer Science in Sport (IACSS 2011), Shanghai, China, 2011*

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Movement Analysis

| 7 | An IMU-based Sensor Network to Continuously Monitor Rowing Technique on the Water  
Bernd Tessendorf, Franz Gravenhorst, Bert Arnrich and Gerhard Tröster  

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Rowing Fingerprints

| 8 | SonicSeat: Design and Evaluation of a Seat Position Tracker based on Ultrasonic Sound Measurements for Rowing Technique Analysis  
Franz Gravenhorst, Christoph Thiem, Bernd Tessendorf, Rolf Adelsberger, Bert Arnrich, Conny Draper, Richard M. Smith, Gerhard Tröster  
In: Springer, Journal of Ambient Intelligence and Humanized Computing, 2014

---

| 9 | Identifying Unique Biomechanical Fingerprints for Rowers and Correlations with Boat Speed – A Data-driven Approach for Rowing Performance Analysis  
Franz Gravenhorst, Amir Muaremi, Conny Draper, Margy Galloway, Gerhard Tröster  
In: *International Journal of Computer Science in Sport, 2015*

Table 2: Publications considered in this thesis (chapters 3 to 9)

1.5 Additional Publications

Besides the mentioned rowing project, the author of this thesis worked on pervasive healthcare topics and was contributor for the EU-funded project “Monitoring and Treatment of Bipolar Disorder Episodes” (MONARCA). The publications resulting from this project as well as additional publications on
other topics that are not included in this thesis are listed in the following overview.

1.5.1 Additional Rowing-Related Publications

- **Calculating Angles with Inertial Measurement Units in Highly Dynamic Sports like Rowing** [48]
  Franz Gravenhorst, Timothy Turner, Conny Draper, Richard M. Smith and Gerhard Tröster
- **SonicSeat: A Seat Position Tracker based on Ultrasonic Sound Measurements for Rowing Technique Analysis** [43]
  Franz Gravenhorst, Christoph Thiem, Bernd Tessendorf, Rolf Adelsberger, Bert Arnrich and Gerhard Tröster
  *in: Proceedings of the 7th International Conference on Body Area Networks (Bodynets), Oslo, Norway, 2012*
- **Towards a Rowing Technique Evaluation Based on Oar Orientation** [45]
  Franz Gravenhorst, Bernd Tessendorf and Gerhard Tröster
  *in: International Conference on Pervasive Computing (Pervasive 2011), San Francisco, CA, USA, 2011*

1.5.2 Gait Analysis for Runners

- **Development of an Android Application to Estimate a Runner’s Mechanical Work in Real Time Using Wearable Technology**
  Christina Strohrmann, Franz Gravenhorst, Severin Latkovic and Gerhard Tröster
  *in: 9. Symposium Sportinformatik, Deutsche Vereinigung für Sportwissenschaft, 2012*

1.5.3 Publications on Pervasive Healthcare

- **Assessing Bipolar Episodes using Speech Cues derived from Phone Calls**
Amir Muaremi, Franz Gravenhorst, Agnes Grunerbl, Bert Arnrich and Gerhard Tröster

in: International Symposium on Pervasive Computing Paradigms for Mental Health (MindCare), Tokyo, Japan, 2014

- Exploring the link between behaviour and health
  Franz Gravenhorst, Amir Muaremi, Venet Osmani and Bert Arnrich

  in: Personal and Ubiquitous Computing (2014)

- Mobile Health Systems for Bipolar Disorder: The relevance of Non-Functional Requirements in MONARCA Project
  Oscar Mayora, Mads Frost, Bert Arnrich, Franz Gravenhorst, Agnes Grunerbl, Amir Muaremi, Venet Osmani, Alessandro Puiatti, Nina Reichwaldt, Corinna Scharnweber and Gerhard Tröster

  in: IGI International Journal of Handheld Computing Research (IJHCR), 5:1(1-12), 2014

- Mobile Phones as Medical Devices in Mental Disorder Treatment
  Franz Gravenhorst, Amir Muaremi, Jakob Bardram, Agnes Gruenerbl, Oscar Mayora, Gabriel Wurzer, Mads Frost, Venet Osmani, Bert Arnrich, Paul Lukowicz and Gerhard Tröster

  in: Personal and Ubiquitous Computing (2014)

- Monitoring the Impact of Stress on the Sleep Patterns of Pilgrims using Wearable Sensors
  Amir Muaremi, Agon Bexheti, Franz Gravenhorst, Bert Arnrich and Gerhard Tröster

  in: IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), Valencia, Spain, 2014

- Personal Health Systems for Bipolar Disorder: Anecdotes, Challenges and Lessons Learnt from MONARCA Project
  Oscar Mayora, Bert Arnrich, Jakob Bardram, Carsten Dräger, Andrea Finke, Mads Frost, Silvia Giordano, Franz Gravenhorst, Agnes Grunerbl, Christian Haring, Reinhold Haux, Paul Lukowicz, Amir Muaremi, Steven Mudda, Stefan Ohler, Alessandro Puiatti, Nina Reichwaldt, Corinna Scharnweber, Gerhard Tröster, Lars Vedel Kessing and Gabriel Wurzer


- Towards a Mobile Galvanic Skin Response Measurement System for Mental Disorder Patients
  Franz Gravenhorst, Amir Muaremi, Agnes Gruenerbl, Bert Arnrich and Gerhard Tröster
1.5.4 Group Behavior Analysis

- **Understanding Aspects of Pilgrimage using Social Networks derived from Smartphones**
  Amir Muaremi, Agon Bexheti, Franz Gravenhorst, Julia Seiter, Sebastian Feese, Bert Arnrich and Gerhard Tröster
  *in: Elsevier Pervasive and Mobile Computing (PMC), 2014*

- **Merging Inhomogeneous Proximity Sensor Systems for Social Network Analysis**
  Amir Muaremi, Franz Gravenhorst, Julia Seiter, Agon Bexheti, Bert Arnrich and Gerhard Tröster
  *in: International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous), Tokyo, Japan, 2013*

- **Monitor Pilgrims: Prayer Activity Recognition using Wearable Sensors**
  Amir Muaremi, Julia Seiter, Franz Gravenhorst, Agon Bexheti, Bert Arnrich and Gerhard Tröster
  *in: International Conference on Body Area Networks (Bodynets), Boston, MA, USA, 2013*

1.5.5 Multimodal Hearing Instruments

- **Design of a Multimodal Hearing System**
  Bernd Tessendorf, Matjaz Debevc, Peter Derleth, Manuela Feilner, Franz Gravenhorst, Daniel Roggen, Thomas Stiefmeier and Gerhard Tröster
  *in: Journal of Computer Science and Information Systems (2013)***
• Exploration of Head Gesture Control for Hearing Instruments
  Bernd Tessendorf, Peter Derleth, Manuela Feilner, Franz Gravenhorst, Daniel Roggen, Thomas Stiefmeier, Christina Strohmann and Gerhard Tröster

• Ear-Worn Reference Data Collection and Annotation for Multimodal Context-Aware Hearing Instruments
  Bernd Tessendorf, Peter Derleth, Manuela Feilner, Franz Gravenhorst, Andreas Kettner, Daniel Roggen, Thomas Stiefmeier and Gerhard Tröster
  in: 34st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2012), San Diego, CA, USA, 2012

1.5.6 Invited Talks

• Unobtrusive Electrodermal Activity Measurements for Monitoring of Bipolar Patients
  Franz Gravenhorst, Amir Muaremi, Bert Arnrich and Gerhard Tröster
  in: Workshop at World Psychiatric Association International Congress (WPAIC), Vienna, Austria, 2013

• Voice Analysis with Mobile Phones for Monitoring of Bipolar Patients
  Amir Muaremi, Franz Gravenhorst, Bert Arnrich and Gerhard Tröster
  in: Workshop at World Psychiatric Association International Congress (WPAIC), Vienna, Austria, 2013

• Tragbare Sensoren für psychische Erkrankungen am Beispiel der Erkennung von Episoden der Bipolaren Affektiven Störung
  Franz Gravenhorst, Amir Muaremi, Bert Arnrich and Gerhard Tröster

• Unobtrusive Electrodermal Activity Measurement Device and Voice Analysis for Supporting Bipolar Disorder Monitoring
  Franz Gravenhorst, Amir Muaremi, Bert Arnrich and Gerhard Tröster
This chapter summarizes the thesis’ contributions to the development of a system for rowing performance analysis. It is divided into three parts. The first part describes the development of components for instrumenting rowing boats. These components include acceleration, gyroscope, magnetic field and ultrasonic sound sensors that are used to record the movements of the boat and the rowing oar. The second part introduces performance metrics and visualizations that support the interpretation of the measured data. Use-cases are given to demonstrate the application and benefits of the post-processed data. The third part extends the focus from analysing individual rowers to analysing a group of rowers. It introduces further data-processing methods that allow the comparison of different rowers. The chapter ends with an overall conclusion and an outlook for possible extensions of the research presented in this thesis.
2.1 Designing Components for Instrumenting Rowing Boats

2.1.1 IMU-based system for sensing oar movements

During the drive phase, the rower fixes the oar in the water and then pulls at the handle to accelerate the boat towards the finish line. The oars can move horizontally, vertically and they can rotate (chapter 1.1). The horizontal oar angle describes the movement of the blade in parallel to the water surface as illustrated in Figure 6. Its range of motion is commonly referred to as the stroke length.

![Figure 6: Horizontal oar movement during the rowing stroke: (c) describes the angle at the start of the rowing stroke, the catch position, (b) describes the angle at the end of the rowing stroke, the finish position, (a) describes the swept angle during the stroke, the geometric stroke length, (d) indicates the direction in which the athlete applies force to the handle. [41]](image)

Stroke length is considered an important factor for determining rowing performance [99]. In measurements with elite rowers on rowing machines stroke length correlated with the rowing speed with a correlation coefficient of 0.76 (p < 0.001) [54]. Rauter et al. analysed the horizontal oar movement and provided real time feedback to optimize mean boat velocity [80]. The state-of-the-art for measuring oar orientation is based on potentiometer-based systems [71]. We wanted to investigate the feasibility of using inertial sensors to compute oar orientations by comparing different
mounting possibilities for the sensors, and different algorithms for post processing of the raw data.

We proposed three different ways to measure the horizontal oar angle based on inertial measurement units. One approach examines commercially available, wired IMU sensors which are attached to the oar [102]. Our second approach is based on a custom-made wireless IMU module which is integrated invisibly into the oar [49]. The third approach makes use of smartphone-integrated sensors and suggests that a smartphones is attached to the oar [42].

Table 3 features a comparison of the three approaches that are described briefly in the following paragraphs and in detail in chapters 3, 4 and 7.

<table>
<thead>
<tr>
<th></th>
<th>IMU on oar [102]</th>
<th>IMU in oar [49]</th>
<th>Smartphone on oar [42]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Price:</strong></td>
<td>$200-$1000</td>
<td>$200-$300</td>
<td>$200</td>
</tr>
<tr>
<td><strong>Accuracy:</strong></td>
<td>++</td>
<td>+++</td>
<td>+</td>
</tr>
<tr>
<td><strong>Handling:</strong></td>
<td>+</td>
<td>+++</td>
<td>++</td>
</tr>
<tr>
<td><strong>Availability:</strong></td>
<td>+</td>
<td>+</td>
<td>+++</td>
</tr>
<tr>
<td><strong>Battery:</strong></td>
<td>2h</td>
<td>&gt;6h</td>
<td>&gt;7h</td>
</tr>
<tr>
<td><strong>Sensor:</strong></td>
<td>Commercial module</td>
<td>Custom-designed module</td>
<td>Smartphone</td>
</tr>
<tr>
<td><strong>Remarks:</strong></td>
<td>Proprietary filters</td>
<td>Invisible</td>
<td>No dedicated hardware necessary</td>
</tr>
</tbody>
</table>

Table 3: Different approaches for IMU-based oar angle measurements implemented in this thesis

2.1.2 IMU module attached to oar

We evaluated different sensor positions, the number of sensors and the sampling rate of the sensors to achieve a reasonable trade-off between the number of required sensors and analysis possibilities. We visualized data
from 12 different sensor locations of 10 recording sessions with 5 participants. We found that three IMUs positioned on both oars and on the boat were sufficient to address our research questions. The sensors on the oar provide the orientation data explained above. The sensor on the boat provides data of the boat’s acceleration and allows us to calculate a differential signal to assure that the oar orientation data is independent of the absolute boat movement, e.g. caused by wavy water or an intentional change of the direction. We filed this innovation successfully as patent [5]. The final setup with three off-the-shelf IMUs (Xsens Technologies) is depicted in Figure 7.

![Figure 7: Measurement setup consists of three IMUs, one in the boat and one to each oar. (a) depicts the general setting [102] © 2011 IEEE, (b) details the attachment to the oar.](image)

Movements in rowing occur quickly, with elite athletes managing to insert the blade in the water at the catch position in as little as 40ms. For our analysis the system’s maximum sampling rate of 60 Hz was sufficient.

Figure 8 depicts typical signals for the three orientation angles measured with an IMU on the oar. The definition for the angles can be found in [102]. The most relevant data such as stroke segmentation and stroke length can be obtained from the horizontal oar angle. The rotational oar angle reveals whether the blade is feathered or squared. The vertical oar angle indicates the depth of the blade relative to the boat.
2.1.3 IMU module inside oar

In our alternative implementation we developed an oar-integrated measurement system. It consists of an oar angle measurement board mounted in a waterproof enclosure which in turn is mounted inside the oar. The oar is modified with the addition of a waterproof battery charging port and power switch (see Figure 9).

Figure 9: IMU inside oar to measure oar angles, dismantled to show, paddle (1), oar angle measurement unit (2), handle with charging port (3) and power switch (4). [49] © 2013 IEEE

Tri-axial acceleration, gyroscope and magnet field sensors on the oar angle measurement board detect changes in the oar’s angular rotation rate, linear acceleration and magnetic field state. The sensor data is transmitted via the Bluetooth protocol to the user interface application running on a waterproof mobile phone mounted with a suction cup holder on the rowing shell (see Figure 10).
To calculate the oar angles from the raw acceleration, gyroscope and compass data, we propose a modified strapdown algorithm [21, 112], optimized for high dynamic motion like rowing.

To validate the accuracy of the measurement system and the algorithm, we deployed the system to a rowing boat and benchmarked its performance against a widely used commercial wired potentiometer-based system [71]. Considering the wired system as a gold standard reference system, the stroke length measurements of our new contactless approach showed errors of $1.56^\circ \pm 0.63^\circ$. The correlation coefficient between both measurements was $0.9989 \pm 0.0005$. The major improvements compared to the potentiometer-based systems are simplified handling and unobtrusiveness, nothing has to be mounted onto the boat, there are no wires and the sensors are completely invisible inside the oar.

2.1.4 Smartphone on oar: “Strap and Row”

Our proposed “Strap and Row” system takes advantage of sensors implemented in smartphones. An Android phone is strapped to the oar (Figure 11) and our phone application is launched, controlling the phone-implemented IMU to log acceleration, gyroscope and magnetic field measurements. The main benefits of this “Strap and Row” approach compared to the other approaches presented (see 2.1.2 and 2.1.3) are its broad availability and minimum setup effort. No dedicated IMU module has to be
obtained as smartphones are in many cases already available. To get started, users only have to install the Android App and strap the phone to the oar.

Three different methods are presented to calculate oar angles from the raw IMU measurements, one state-of-the-art method and two novel methods. To evaluate the “Strap and Row” system, we deployed it to an indoor rowing simulator [103, 107, 106] and performed a single-user study. The recorded raw sensor data has been post-processed with each of the three mentioned methods and the results compared to the reference output of the rowing simulator.

State-of-the-art strapdown algorithm. The result showed that the Android-implemented native strapdown algorithm [26] was not usable as it delivered inconsistent measurements with errors of more than 100%. While the native strapdown algorithm is designed to deliver estimations in unrestricted conditions [21], the two novel methods are specifically designed for the movement of rowing. Considering rowing as a periodic movement, we can exploit this application-specific knowledge to improve the angle calculations.

Catch-reset strapdown algorithm. This method detects the beginning of each stroke, the catch position, and resets the integration of the angular velocity at these time points periodically. Evaluated against the rowing simulator measurements, this algorithm scored an average stroke length error of 8.07° for stroke lengths between 35° and 88°. Figure 12 illustrates...
the measured angles and errors. The error can be identified as a constant offset error for each measurement, the relative changes in stroke lengths were represented consistently.

Figure 12: Evaluation of the proposed catch-reset strapdown algorithm. 55 pairs of bars represent the 55 strokes. The left bar (red) of each pair represents the stroke length measured by the reference system, the right one (blue) the results of the catch-reset strapdown algorithm.

Finish-reset strapdown algorithm. This method works analogically to the catch-reset strapdown algorithm, but performs resets at the end of the stroke, the finish positions. This method scored an average stroke length error of 7.64°. This approach failed to quantify changes in stroke lengths consistently. As visualized in Figure 13, the measured stroke length for 54 of the 55 strokes is in the range of 69° to 83° although the actual ground truth lengths cover a range of 35° to 88°. One reason for this inaccuracy is the mismatch between the actual finish position and the detected on-set of the feathering movement. Further analysis can be found in chapter 3.
Figure 13: Evaluation of the proposed finish-reset strapdown algorithm. 55 pairs of bars represent the 55 strokes. The left bar (red) of each pair represents the stroke length measured by the reference system, the right one (blue) the results of the finish-reset strapdown algorithm.

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2.1.5 Seat position tracker based on IMUs

The legs generate most of a stroke’s power [47]. The movement of the sliding seat is linked to the rower’s leg movement. The trajectory of the seat position over time is a key element in rowing technique.

We presented a seat position tracker system which consists of two miniaturized measurement units; one is attached to the sliding seat and one to the boat shell (Figure 14).

Each unit features a tri-axial accelerometer and magnetometer. We present a method for processing the measurement data to calculate the seat position. The magnetometer data is used to correct for offset and drift errors. Three accelerometer axes and prior knowledge concerning movement restrictions is exploited to introduce a dynamic calibration algorithm, which identifies and corrects for orientation misalignments between the two mounted sensor nodes. It is based on Kirkpatrick’s Simulated Annealing optimization algorithm [59] and works without any dedicated calibration movements or need to attach the sensors in an accurately, well-defined position or angle. The magnetometer-based drift cancellation and the dy-
namic misalignment correction improve to the system’s measurement accuracy and usability.

Figure 14: Acceleration based sliding seat position tracker, schematic (b) and mounted in a rowing boat (a). The system consists of two synchronized tri-axial acceleration sensors: one of them is attached to the bottom of the sliding seat (2) and the other sensor module is fixed to the boat shell (3). For offset error compensation, the system is supplemented with a permanent magnet (1) attached to the seat and a reed switch (4) attached to the boat and wired to the sensor module (3). [47]

We implemented the devised system and performed a proof-of-concept data recording on the water. Figure 15 includes an excerpt of the recorded data and demonstrates the necessity of the drift cancellation filter.
Figure 15: Comparison of seat position calculation with and without drift cancellation algorithm. Horizontal black lines indicate the discrete time points at which the seat position is detected by the magnetic switch and the compensated solution (blue line) is corrected accordingly. The sensor starts drifting at t=8s resulting in an erroneous trajectory for the uncompensated position. [47]

The main improvement of this seat position tracker method compared to the state-of-the-art [63, 96] is the contactless measurement method, no wires or cords are connected to the sliding seat.

2.1.6 Seat position tracker based on UltraSonic

We developed “SonicSeat”, a contactless seat position tracker for rowing boats based on ultrasonic sound measurements. A commercially available ultrasonic transceiver module is aligned to the boat with the ultrasonic beam pointing towards the sliding seat as depicted in Figure 16. The module sends out sound bursts at a frequency of 40 kHz and measures the time interval until the echo is received. In a post-processing step, the trajectory of the seat position is computed.
To evaluate the accuracy of the measurements, we opted for an indoor rowing simulator setup [103] which allows for the simultaneous recording of the seat position by our SonicSeat system as well as with a state-of-the-art optical motion tracking system (QTM, Qualisys AB, Gothenburg, Sweden).

In total, we recorded 51 strokes which included four different stroke lengths and a variety of common mistakes, such as delay at the finish position, delay at the catch position or fast sliding during the recovery phase.
Both systems, the SonicSeat as well as the optical reference system, experienced no data loss and both systems identified all 51 strokes. Considering the optical motion tracker as “gold standard”, we compared its measurements with the SonicSeat recordings. Our system scored an average seat displacement error of 1.13% with a standard deviation of 0.75%. The main advantage of this approach in comparison to the other presented seat tracker (chapter 2.1.5) and the state-of-the-art is the fact that nothing has to be modified or attached to the sliding seat, which means the system does not hinder the rowers’ natural movements.

2.1.7 Boat movement analysis with gyroscopes

Any unintentional variation to the boat’s orientation is defined as instability and leads to an increase in drag forces and a loss of energy [92, 105]. The stability of the boat’s movement is considered crucial to its performance [15, 37]. To measure changes in the boat’s orientation we deployed a miniaturized wireless IMU sensor [51, 101] inside the boat shell. This module (Figure 17) samples angular velocities in all three dimensions and stores it in a local non-volatile memory.

Figure 17: Wireless IMU module which is attached to the boat to record angular velocities. [44]

We considered time intervals of 10 strokes and proposed three different metrics to quantify boat stability: average amplitude, standard deviation and the range (maximum minus minimum) of the angular velocity. This is done separately for each of the three axes of the gyroscope. The definitions of the three possible turning directions are illustrated in Figure 18.
In collaboration with Swiss national rowing team coaches we equipped two rowing boats, boat A and boat B, for world level athletes with our measurement system. Based on collected data during test races we benchmarked the boats in respect to their stability for the given crew.

All three proposed performance metrics of the pitch angular velocity of boat A were at least 38% smaller than the corresponding ones of boat B. Similar results were obtained for the performance metrics of the roll and yaw angular velocities. Manual stopwatch measurements indicated that boat A also moved faster than boat B, although the crew was more experienced with rowing in boat B. Details can be found in chapter 6.

2.2 Performance Analysis using Rowing Sensor Data

In this chapter we present analyses that were carried out based on the datasets we recorded with our sensor oar and seat movement measurement systems (chapter 2.1.1 and 2.1.6). We propose visualization methods to illustrate differences in the rowing movement of top-level athletes and demonstrate how obtained data can be used to support coaching.

2.2.1 Case studies based on oar measurements

**Stroke Rate and Stroke Length.** Figure 19 depicts the stroke length over the stroke rate for two rowers, R1 and R2, during both training and racing. Both athletes are experienced rowers, R1 is a current Olympic silver medal-
Alist and R2 is a current U23 world champion. The stroke length decreases as the stroke rate increases for both R1 and R2. During races a broader range of stroke rates occurs as compared to training. The race starts and finishes with sprint phases, which means there are higher stroke rates achieved during these phases of the race. The race phases are represented in clusters and are marked with colours exemplarily for R1. Here we observe a linear correlation between stroke rate and stroke length. The corresponding slope is lower for R1 than for R2. This means that R1 can keep a higher stroke length, even at an increased stroke rate. R1 shows a low variance in the stroke length and stroke rate and a high absolute stroke length and maximum stroke rate. In the steady-state race phase R1 and R2 follow two different rowing styles: R1 performs longer strokes at a lower stroke rate compared to R2. R2 compensates the shorter stroke length with a higher stroke rate. During training the stroke rates of R1 and R2 are similar, but R1 performs a longer stroke and also manages to control the movement more precisely and consistently than R2.

**Detailed Analysis of Stroke Length.** Coaches can use our oar measurement system to analyse variations in stroke length in more detail. The variation of the stroke length might result from a variation in the catch position, the finish position or both. Figure 20 depicts the horizontal oar angle over time.
for rower R3 over 33 strokes. In this example the catch position ranges between -56.4 and -51.6° with a standard deviation of 1.2°. The finish position ranges between 50° and 60° with a standard deviation of 2.4°. The variance in the finish position is the main contributor to the variability of the overall stroke length. Based on this analysis the coach is able to advise the rower to perform dedicated exercises to strengthen the muscles which support a stable finish position.

Figure 20: Stroke length is shown in detail: In this example the variability of the stroke length results mainly from a variance in the finish position. [102] © 2011 IEEE

**Oar Rotation.** Figure 21 depicts the oar rotation angle over the horizontal oar angle. This visualization supports the coach in analysing the consistency of the squaring movement and helps to identify rowers who square early or late. The precision of the feathering and squaring motion is also characterized. In this example we can observe an over-rotation by R2 after extracting the blade from the water.
2.2.2 Stroke classification based on sliding seat movement

**Seat movement metrics.** As outlined in chapter 1.1 the movement of the sliding seat plays an essential role in good rowing technique. Based on qualitative descriptions in the literature [15, 35, 37], and in collaboration with national rowing coaches from Germany and Switzerland we propose measures that quantitatively represent the rower’s seat movement performance. A selection of the proposed metrics is visualized in Figure 22.

**Catch delay.** In the catch position the centre of gravity is located at the stern of the boat. The longer the pause in this position, the more the boat’s stern rotates into the water and decelerates the boat. Therefore, the blade should go into the water and start the next stroke as soon as the most forward position, the catch, is reached [37]. The catch delay should be as short as possible.

We define the catch delay \( \Delta t_{\text{delay},n} \) as the length of the time interval during which the seat position resides at the catch position or within the range of \( \pm \Delta h_{\text{tol}} = 4 \, \text{cm} \).
Stroke classification. We recorded the seat movement during 223 complete strokes of an on-water rowing session with one male rower. The rower was accompanied by a coach in a motorboat who prompted him to perform several technical drills aimed to provoke either good technique or typical mistakes such as catch delay. After the training session, we asked two experienced elite level (world cup) rowers to decide solely based on the recorded video footage which strokes were “significantly worse (=longer catch delay) than average” for the given dataset. The remaining strokes were rated as “average”. They had to agree upon a common rating for each stroke. We considered the experts’ rating as gold standard and compared it to the result of our classifier. The input values for our classifier
were the catch delays extracted from the recorded seat trajectories. Our binary classifier compares each catch delay with a dynamic threshold and rates each catch delay that exceeds the threshold as “worse than average” (details in chapter 8). This classifier achieved a specificity of 90% and a sensitivity of 100%. An excerpt of the seat trajectories for approximately 50 strokes and the corresponding classifications is depicted in Figure 23.

![Figure 23: Comparison of classifier with experts’ rating. Red background colour means that experts rated the catch delay of the stroke as “worse than average”. Red circles represent the concordant rating of the classifier.](image)

Our measurement system combined with the proposed classification method allows for the identification of the worst strokes when looking at the catch delay. This information can be used for real-time feedback or for post-training analyses to focus attention on the strokes that have the most potential for improvement and trigger technical drills.

### 2.3 Data-Driven Identification of Rowing Fingerprints

**Rowing Fingerprint.** In the course of deploying sensors and data-processing methods [41], we generated 74 boat-specific and 56 oar-specific features.
In this subchapter we identify which features from these 130 proposed features were the most relevant for identifying differences within a given group of rowers. We define this subset of features as the biomechanical fingerprint of a rower. Different groups of rowers have different relevant features. Different rowers within a group of rowers have the same feature subset but the values are different. The fingerprint should fulfil the following requirements:

1. Uniqueness: The values of the selected feature subset should be most discriminative for each rower. This means that by knowing the values of these features, the rower can be identified.

2. Constant: The values of the selected features do not depend on the crew partner. For each rower, the values of the selected features stay within a specific and individual range, even when put together in crew boats with other rowers.

**Feature selection.** To identify the features that are most unique for each rower we implemented three different classifiers and performed wrapper-based feature selection. The classification algorithms were: k-Nearest Neighbours (kNN) [16], Support Vector Machines (SVM) [30] and Random Forests (RF) [73].

The overall structure of the iterative feature selection process is depicted in Figure 24. In a first step we generate a subset of features using sequential forward feature selection (SFFS) [56]. Then, each subset is evaluated using a wrapper-based approach [113]. These two steps are repeated until the SFFS is finished. For our case with \( m = 130 \) original features there are \( N = \frac{m(m+1)}{2} = 8515 \) iterations necessary.

**Example.** We applied the proposed method to data recorded from four Olympic-level female rowers (A, B, C and D). These athletes were racing together in double scull boats. The boats were equipped with angle and force sensors attached to each rowing oar as well as a GPS, accelerometer and gyroscope measurement module mounted on the boat. During a 6-day rowing camp, the athletes performed a race over 2000m every other day. This way, each of the six possible crew combinations had one race. Each race course was segmented into 50m intervals and for each segment and
each rower 130 features were computed (details in chapter 9). For each of
the 4 classes (4 rowers) we end up with \( M = 3 \cdot \frac{2000}{50} = 120 \) feature vec-
tors, in total there are \( 4 \cdot 120 \cdot 130 = 62400 \) feature values.

Using the feature selection approach (Figure 24) for each of the three pro-
posed classifiers a ranking of the most discriminant features was calculat-
ed. The evaluation criterion was classification accuracy, meaning the share
of race segments for which the classifier correctly identified the rower from
whom the data was generated. The dependency between the number of
considered features and the achieved accuracy for each of the three classi-
fiers is shown in Figure 25.

The “Finish Slip” feature, which describes the rower’s efficiency at the end
of the rowing stroke, turned out to be the most discriminative feature for
all three tested feature selection methods. The k-Nearest Neighbour classi-
ifier outperformed the Random Forests and Support Vector Machine classi-
fiers in terms of rower identification accuracy. In a 3-fold cross-validation
the kNN classifier achieved an identification accuracy of 74.6% solely based
on the Finish Slip feature. The calculation of this feature only requires oar orientation sensors. Applying one or two additional features this accuracy improved to 90.7% or 95.6% respectively. However, the calculation of these additional features requires an additional boat sensor to acquire boat accelerations. None of the boat-specific features such as stability or boat acceleration ranked within the top-five features for discriminating a rower. Rower’s individual characteristics can be found primarily in their oar movement rather than their impact on the boat drive or stability.

![Graph](image)

Figure 25: Visualization of how accurately a rower can be identified with a defined biomechanical fingerprint. The more features that are allowed in the fingerprint, the more accurately the rower can be identified. The results are plotted for three different classifiers (kNN, RF, SVM).

[41]

Figure 26a depicts the values of the two most discriminative features. One point in the plot corresponds to one rower during one race segment. The four colours indicate the identities of the athletes (A, B, C or D). The six different shapes of the point markers correspond to crew combinations. For example, squares are available in red and black. These points correspond to the race segments in which rower A (red) and rower C (black) were rowing the double together.
Figure 26: Distribution of the two most discriminative features (“Finish Slip” and “Angular Drive Acceleration Point”) for a group of four rowers rowing together pairwise in crew boats, (a) shows the distribution of the two most discriminative features. One marker corresponds to averaged features of one rower during one race segment. Different colours indicate different rowers. The same marker shapes indicate the same crew combinations. (b) Each of the 80% confidence ellipses include the race segments of two rowers when rowing together. The compactness of the ellipses depict how similar the two rowers were rowing for each crew combination. [41]

Looking at the distribution of the different athletes (colours), each rower occupies a dedicated area and forms a cluster which partly overlaps with
other rowers’ clusters. For each rower, the values of the two features stay within individual and characteristic ranges.

Figure 26b visualizes covariance error ellipses [55, 100]. Each ellipse includes the race segment of both rower of one crew combination. When compared to the other groups, the ellipse BA is the most compact one, covering the smallest surface area. This illustrates, that these two rowers are most similar and consistent over time concerning the two considered features (“Finish Slip” and “Angular Drive Acceleration Point”). These two rowers also scored the fastest time over the 2000m race distance, faster than all the other combinations within the group and later received an Olympic medal.

2.4 Conclusion

We proposed sensing, post-processing and visualization approaches and investigated their application in performance analysis in rowing. As opposed to the state-of-the-art we focused on unobtrusive technology that requires less installation and calibration efforts and has the potential to make rowing performance analysis accessible to a broader part of the rowing community.

- We introduced and evaluated three different implementations for measuring the horizontal oar angle with IMU sensing. We showed that smartphones strapped onto rowing oars can be used for rough qualitative measurements. For more accurate measurements we suggest the use of custom-designed IMU modules that can be fully hidden inside the oar.
- The state-of-the-art strapdown algorithm to calculate orientations from IMU data cannot be used for our proposed oar angle measurement systems. We suggested modifications which incorporate rowing-specific movement restrictions and evaluated the performance in real-life data recordings.
- Two contactless measurement setups for tracking of the seat position are introduced, based on acceleration and ultrasonic sound
sensors. Post-processing algorithms for both setups were optimized using domain-specific knowledge. The usability was proven in on-water experiments.

- We instrumented boats with gyroscope sensors and proposed metrics to quantify boat stability. We applied the method to identify the most stable boat for a given crew.
- We show how machine-learning approaches can be used to identify the most discriminative rowing specific metrics for a group of athletes. We present an example how this approach was applied for a crew selection task.
- In collaboration with national teams of Switzerland, Australia and Germany, we recorded data and demonstrated with exemplary case studies how our proposed systems are used by Olympic-level rowing coaches, biomechanists and athletes.

2.5 Outlook

Our vision is to build a boat area network with a set of sensor nodes that enable real-time feedback for the coaches and athletes and that is practical for daily use in training sessions.

The presented implementations, evaluations and case studies are a first step towards this vision. The continuing miniaturization and increasing availability of inertial measurement units are a driving factor in the development of sensor systems for sports applications. We believe that bridging the boundaries of ubiquitous computing and sports science can further develop the sports.

Specifically, we suggest the extensions of our presented research in three directions:

**Sensors.** In future studies the number of sensors and thus the number of available performance metrics should be increased. A broader set of features could offer new insights. This way, the results of the proposed post-processing approaches can be further fine-tuned and features describing boat-movements can be broken down into actual causes. For example
instead of features describing the overall oar movement, measurements of the leg, upper body and arm movements can be included. The right body posture is not only essential for achieving high boat speed, it also helps to avoid injuries.

**Subjects.** In our presented work we focused on methods. Although case studies have been performed to visualize the approaches, the number of subjects was limited and therefore the results are specific for the presented examples. Further studies with more subjects will add more data to the database making the results statistically relevant. We could build up representative and generalizable rules. Specifically, we are interested in applying the methods and investigating the differences in results for male rowers, bigger crew boats, lightweight rowers and sweep rowing. Additionally, time-dependency can be considered in order to account for anomalies due to sprint phases during races or different degrees of fatigue during training. We would also like to further explore whether the position that a rower is seated in within a crew influences his/her biomechanical fingerprint.

**Feedback.** Our work focused on methods to sense and post-process rowing performance data. Feedback in most cases was given in a visual way during post-training analyses. In a next step, the system should be extended with more real-time feedback and more diverse feedback modalities. Approaches such as haptic or auditory feedback appear to be promising [91].
Chapter 3  Strap and Row: Rowing Technique Analysis with Mobile Phones

Franz Gravenhorst, Amir Muaremi, Felix Kottmann, Roland Sigrist, Nicolas Gerig, Conny Draper, Gerhard Tröster

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Abstract

The length of a rowing stroke is an important performance metric for athletes and coaches. Accurate measurements are possible with optical or mechanical systems, which require significant setup effort. This work presents a new approach using a smart phone as a sensor device that is strapped to the oar. Two algorithms are introduced to calculate stroke lengths from the raw phone sensor data. The performance of each algorithm is evaluated by comparing the results to a mechanical reference system. Data was recorded during a single-user study performed on a rowing simulator. The best algorithm showed an average stroke length error of $7.64^\circ \pm 2.95^\circ$.

3.1 Introduction

3.1.1 Motivation

Physical strength and proper technique are the two key components for fast and healthy rowers. While there are many unsupervised methods available for increasing strength and endurance, the improvement of rowing technique requires the frequent availability of a human coach.

Technical tools for advanced rowing technique analysis are in most cases expensive and difficult to operate. These tools usually consist of dedicated sensor hardware and recording or feedback devices that have to be installed in the rowing boat. At the same time, motion sensors are becoming increasingly integrated into our daily lives through mobile accessories such as smart phones and watches. Consequently, instead of introducing new dedicated sensor hardware for rowing, we want to research the extent to which low-cost sensors like accelerometers and gyroscopes can be used for rowing technique analysis.

The most established mobile sensor platform that features accelerometers and gyroscopes are smart phones, which can additionally serve as a logging, broadcasting or even feedback device.
To ensure a realistic application scenario for non-professional athletes we follow a “strap and go” approach. The proposed system should work without introductory user-specific learning or calibration phases. Ideally, the rower simply straps the phone onto their rowing oar, opens the app and starts rowing.

3.1.2 Rowing Basics

Rowing is a continuous repetition of stroke cycles in which the rower moves the rowing oars through the water. Rowers sit on a moveable seat that slides backwards and forwards on tracks, enabling them to use their legs to extend the stroke length. Each rowing stroke can be segmented into two phases, the drive phase and the recovery.

To begin the drive phase, the rower moves the sliding seat to the most forward position possible on the slide, bending his/her legs and reaching out with the arms. In this position, called the “catch”, the rower squares the blades and places them into the water. By pushing the legs, the rower applies force to the oars’ handles and moves his/her seat to the bow of the boat. The drive phase is finished by pulling the handles towards the body. The most backward position of the handle is reached when the arms are fully bent and the legs fully extended. At this position, the “finish”, the rower lifts the blades out of the water and feathers the blades. This is the transition from the drive to recovery phase. During this phase, the athlete moves the blades again to the catch position by extending the arms and bending the legs. Then, the next stroke begins.

It is beneficial to both competitive and recreational rowers to master a consistent stroke pattern with good stroke length (Figure 27) and smooth transitions. Improving technique is an important part of rowing training for beginners as well as world champions. Obtaining proper technique is important for recreational rowers to avoid injuries and increase their capacity to practice the sport for a long time without health issues. Professional athletes seek to maintain proper technique even when exhausted or rowing at high stroke rates.
3.1.3 State of the Art

Rowing technique and performance analysis using electronic evaluation has been pursued by science for a long time. One of the first approaches was carried out by Schneider [86], who used telemetry and post-recording evaluation. Gyroscope sensors were first used in [105]. They were attached to the boat in order to analyze boat stability. Due to the weight and form factor of the early versions of these sensors, it was not feasible to attach them to rowing oars. With today's mobile devices and smart phones, the option of onboard evaluation and feedback in real time has become possible. Sabatino et al [83] describe a feedback measurement system, in which a piezoelectric gyro is used. It consists of two Palm handhelds, one in the boat and one for the coach. Bonnet et al [25] focus on decreasing the drift problems of gyros for runners using a weighted Fourier linear combiner filter to create an estimation of the 3D orientation. Kleshnev [60, 62] worked on the kinematics of rowing to classify what a good rowing stroke is, as well as Smith et al [95]. Nolte’s research finds optimal stroke lengths according to different shapes of the oar [75]. He achieves this by concentrating on acceleration and oar/scull angles, which are measured with potentiometers. Several feedback methods and the suitable data processing approaches are discussed and compared to the traditional rower/coach feedback in [61]. An additional approach for classifying stroke lengths is described in [58], where body sensor gyros placed at the femur and lower back record the moves of the rowing stroke. In this approach, rowing technique is classified between good and poor technique. Another research
group also focused on stroke length measurement with IMUs [68] by implementing the system 'Remote', which is compared to a commercial measurement system. The results promise a high potential of IMU measurement systems for movement analysis in rowing.

In our own previous work we developed the concept of a boat area network where commercial IMUs with proprietary strap-down algorithms are used to calculate oar and boat angles [102]. In another work, we evaluated the use of custom-designed IMUs that are implanted in rowing oars and connect wirelessly to a feedback device in the boat [49].

### 3.1.4 Contribution

This work contributes to the state-of-the-art in the following respects:

- Strap and Row approach is introduced as a practical method that takes advantage of sensors implemented in smart phones for basic qualitative rowing technique analysis.
- Two new rowing-specific realtime-enabled strapdown algorithms are proposed to calculate horizontal oar angle trajectories from acceleration and angular velocity measurements.
- Performances of the two new rowing-specific algorithms and a general purpose algorithm are evaluated with reference measurements on a rowing simulator.

### 3.1.5 Paper Organization

We use a smart phone as sensor device. The requirements and software implementation methods for data collection are described in the next section. To evaluate the measurements taken with our new system, we compare them to reference measurements obtained with an indoor rowing simulator. The system and the experiment setup are described in section 3.3. Section 3.4 describes approaches of how to use raw data from the phone implemented sensors to calculate oar angles. Data recordings are obtained during a feasibility study as mentioned in section 3.5. The results
are discussed in section 3.6. Next, the limitations of the suggested approach are outlined. Finally, the last section draws conclusions and provides an outlook.

3.2 Mobile Phone as Sensor Device

3.2.1 Requirements

A sensor device used for the proposed angle calculation algorithms, which are introduced later, should ideally meet the following main requirements:

- **Hardware**: The device has to feature three-axis gyroscopes and accelerometers. It should be able to process the data with a sampling frequency of 50Hz. Storage volume and battery capacity should ensure a continuous runtime of at least 120 minutes, which is the maximum duration of a rowing practice.

- **Obtrusiveness**: The sensor should be lightweight and small so that it interferes as little as possible with the rowing movements. Ideally, the athlete should not feel the presence of the sensors and will row as though in a boat without instruments.

- **Handling**: To be useful for a broad number of rowers, the system should be easy to install and intuitive to use.

3.2.2 Android Phone and Data Acquisition App

We chose an Android based mobile phone as recording device because of its broad availability, open development system and price advantage compared to iOS phones. Android is also increasingly used for non-phone devices such as tablets or smart watches, which can easily be substituted for the phone device in our setup. Accelerometers are included in most currently available Android devices. Additionally, gyroscopes are available in the most recent generations of phones. We used the Samsung Galaxy SIII mini for our studies. The Android operating system does not allow for defining a specific sampling frequency, it is only possible to request a qualita-
tively low, medium or maximum frequency. The actual quantitative frequencies on Android devices vary with available resources. They differ from device to device and also slightly within one recording depending on the system usage of the other applications. When we set the sampling frequency to maximum (SENSOR_DELAY_FASTEST), our chosen device delivered in average 102 Hz and reliably at least 100 Hz.

We implemented a lightweight Android application, which stores the sampled sensor data as data files to the phone’s memory. Each set of sampled data is stored together with a timestamp specifying the sampling time as nanoseconds since system boot. Android API also offers a built-in general purpose solution to calculate orientation angles out of the raw sensor data, these values are also recorded for later comparison with our custom-designed algorithms. For annotation purposes and to recall the instructions given during the experiment, the phone’s audio is stored as well. Magnetic field sensors are also included in the phone and this data is taken into account for the built-in angle calculation solution.

The GUI of the app consists of a button to start and stop the recording.

### 3.2.3 Estimation of Oar Angles

After the data recording, the files are transferred via USB to a computer (Lenovo T400, Intel Core 2 Duo P8400, 2x 2,26 GHz, 2 GB RAM). The analysis is performed offline with Matlab R2010a according to the algorithms described in section IV.

### 3.3 Experiment Setup with Simulated Rowing

#### 3.3.1 Rowing Simulator

For the validation of our proposed phone-based application, the sweep rowing simulator of the Sensory-Motor Systems Lab, ETH Zurich, was used [103]. In the middle of a Cave Automated Virtual Environment (CAVE), the rower was seated in a trimmed rowing boat manipulating a real, trimmed
sweep oar with both hands. A virtual river scenario was projected (self-programmed on Unity Pro, Unity Technologies, San Francisco, USA) onto three screens (4m x 3m, projectors: Projection Design F3+, Norway) surrounding the rower. On common loudspeakers, realistic auditory oar-water-interaction was rendered (self-programmed; C++). In addition to the virtual landscape and soundscape, a custom-made tendon-based parallel robot [103, 81] was connected to the trimmed oar in order to render haptic interaction with virtual water. Five drive trains of the tendon-based parallel robot were used to actuate the trimmed oar [81]. Each of the five motorized winches placed outside the CAVE was connected by a rope (4mm “D-Pro Dyneema”, Rosenberger Tauwerk GmbH, Lichtenberg, Germany) over deflection units and a force sensor (K100.2k, Transmetra GmbH, Neuhausen am Rheinfall, Germany) with the trimmed oar. The haptic interaction of the oar with the water was controlled by a Matlab/Simulink® model running at 1kHz on an XPC-target.

![Figure 28: Rowing Simulator setup with HD video camera (1) and mobile phone (2) strapped around the oar (3). © 2014 IEEE](image)

The end-effector position of the oar was calculated by forward kinematics [104] and used to render the haptic interaction between oar and water. The calculations reached an accuracy of ≈ 0.01m, which corresponds to an accuracy of the horizontal and vertical oar angle of ~0.5°. A third oar angle, i.e. the rotation of the blade around the longitudinal oar axis was measured by two wire potentiometers (Micro-Epsilon, WPS-1250-MK4) wound around the oar with accuracy higher than 10°. For the current measure-
ments, simulator data was recorded at 100Hz. A picture of the experiment setup with the rowing simulator is shown in Figure 28.

Even though starboard and portside sweep rowing can be simulated in the current version of the simulator, all measurements of the current study were performed on portside. In previous studies with novice and expert rowers, the rowing simulation was shown to be highly realistic [107, 106].

3.3.2 Mobile Phone Mounting: Strap and Row

The presented mobile phone based measurement system focuses on usability in real-life application. Our vision is a “Strap and Row” approach, which means the measurement can start as soon as the phone is strapped around the inboard part of the rowing oar.

Calibration or adaptation phases are not necessary. In the squared position, the phone is strapped on top of the rowing oar with the screen facing to the sky. In case the phone is not waterproof, it is put it in a waterproof bag before strapping it on. A photo of the setup is shown in Figure 29. To begin recording, the rower opens the app on the smart phone and hits the “Start” button.

Figure 29: Strap and Row approach: Mobile phone (2) is put in a plastic bag for water protection and then strapped tightly around the oar (1). © 2014 IEEE
3.4  Self-Resetting Oar Angle Calculation

3.4.1  Android Native Strapdown Algorithm

There are several approaches to calculate orientation angles from the raw IMU sensor measurements. These so-called strap-down algorithms mainly focus on numerically integrating the angular velocity of the gyroscope. To find the initial orientation and to correct for long-term drift errors, the data from the accelerometers and magnetic field sensors are taken into account. One of these general purpose strapdown algorithms is already implemented in Android’s API. For our application the most intuitive way to follow would be to use the output from the Android API and directly interpret the appropriate Euler angle output as horizontal rowing angle. We compare this state-of-the-art algorithm against two new approaches, which are explained in the following subchapters. All algorithms can be executed in real-time as they are computationally lightweight and no future data is taken into account.

3.4.2  Integration Reset at the Catch Position

This method is again based on the numerical integration of angular velocity data. To correct for the drift error, we assume the catch position to always be at the same oar angle. We define this oar angle as zero. We detect the catch positions and reset the numerical integration of the oar angles to zero each time this position is reached. The catch position is detected each time when both of the following conditions are met:

1. The angular velocity of the horizontal oar angle changes its sign from negative to positive.
2. The acceleration of the phone’s z axis shows at least half the earth gravity.

Condition (1) means the oar movement changes its direction; it indicates the transition between the end of moving the handle forward to the catch and the start of moving it backwards in the drive phase. Condition (2)
makes sure that the oar is squared, another prerequisite for starting the drive phase. Condition (1) could also be met accidentally when a wave hits the blade earlier in the recovery phase – but then the blade is usually feathered, thus condition (2) is not met and a false-detection is prevented. On the other hand, condition (2) alone would be not sufficient as the blade is also squared at other times of the stroke. The combination of both conditions helps to ensure that the correct turning point of the oar direction is identified and false-detections are minimized. A visualization of the catch position detection algorithm is shown in Figure 30.

![Figure 30: Catch position detection algorithm: The change of sign of the angular velocity from negative to positive values is detected as catch position (diamonds), the ground truth catch position are marked with squares. © 2014 IEEE](image)

### 3.4.3 Integration Reset at the Finish Position

This method is similar to the one presented in the previous paragraph and is again based on numerical angle integration and resets at specifics times. This time, the zero point of the angle is defined at the finish position. Unfortunately, the change of sign of the angular velocity from positive to negative is not appropriate for the detection of the finish position as the slope of the gyro data at this time interval is quite flat and noisy (see Figure 30).
Consequently, it would result in false-detections and inconsistent results. Therefore, we decided to use the feathering movement of the oar as an estimation of the finish position. Feathering usually happens just after the finish position is reached and can be detected by looking at the acceleration data of the phone’s z-axis. As soon as this value becomes negative, the finish position is assumed.

An example for the detected points is shown in Figure 31. As expected, the detected finish positions occur shortly after the actual ones.

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Figure 31: Finish position detection algorithm: The actual finish positions (squares) are estimated with the on-set of the feathering movement which is detected as first negative value of the acceleration of the phone’s z axis (diamonds). © 2014 IEEE

### 3.5 Feasibility Study

#### 3.5.1 Study Design

To evaluate the feasibility of the proposed rowing analysis system, we performed a single-user study with an experienced national-level rower. The experiment was approved by the ethics committee of ETH Zurich. The subject participated voluntary and gave written informed consent.
The measurement session was recorded by the reference system in the rowing simulator, the mobile phone based system and an HD video camera (see Fig. 2). The main parts of the session are:

1. Subject receives an introduction to the rowing simulator, including security and safety information.
2. Subject is instructed to row normally to warm up and become familiar with the rowing simulator environment. Once the subject feels s/he is ready, the experiment starts.
3. The phone recording device, reference system and the video camera are switched on.
4. The subject is instructed to do the ‘build-up’ drill. This is a common exercise for rowing technique training and involves different stroke lengths.

An excerpt of the horizontal oar angle data from the reference system is shown in Figure 32.

Figure 32: Excerpt of data from the reference system for the build-up drill. This technique drill involves several sets of strokes with increasing stroke lengths. © 2014 IEEE
3.5.2 Results

To evaluate the proposed methods, we compared the measured data with the data from the reference system. Stroke lengths were calculated as angular offsets between minimum and maximum of the horizontal oar angle (Figure 28) during one stroke. In total the subject performed 55 strokes with stroke lengths between 35° and 88°. The length varied between 0 to 30% from one stroke to the next.

3.5.2.1 Android Native Strapdown Algorithm

An excerpt of the appropriate Euler angle, which corresponds to the horizontal oar angle, is plotted in Figure 33. The changing stroke lengths visible in the reference system are not represented in the measured phone data.

![Figure 33: Oar angle calculated with general-purpose strap-down algorithm included in Android API (a) and for comparison the ground truth of the same strokes with reference system (b). © 2014 IEEE](image-url)
3.5.2.2 Integration Reset at the Catch Position

With this method, the calculated stroke lengths are on average 7.64° smaller than the reference system’s lengths. Standard deviation of the error is 2.95°. The results are visualized in Figure 34.

![Figure 34: Evaluation of the proposed angle calculation method with resets at catch positions. 55 pairs of bars represent the 55 strokes. The left bar of each pair represents the stroke length measured by the reference system, the right one the results of the new proposed method. © 2014 IEEE](image)

3.5.2.3 Integration Reset at the Finish Position

Applying the finish resets, the calculated stroke lengths are on average 8.07° longer than the reference system, the standard deviation of the error is 11.71°. The results are visualized in Figure 35.

3.6 Discussion

The strap-down algorithm, which is implemented in Android’s API is a general purpose algorithm designed to deliver rough estimations in unrestricted conditions. It takes magnetic field measurements into account, which stabilizes orientation measurements in static postures but makes the algorithm fail for high dynamic movements like rowing.
Considering rowing as a non-random and periodic movement, we can exploit this knowledge to improve the angle calculations. The approach with integration resets at the finish position detects the stroke’s reliably, however it cannot quantify changes in stroke lengths consistently. As visualized in Figure 34, the measured stroke length is similar for all strokes although the actual ground truth length increases over the course of the measurement by 151%. The main reason for this inaccuracy is the mismatch between the actual finish position and the detected on-set of the feathering movement (Figure 31).

The method with resets at catch positions constantly underestimates the actual absolute stroke length but does reliably capture qualitative trends such as increasing stroke lengths.

Figure 35: Evaluation of the proposed angle calculation method with resets at finish positions. 55 pairs of bars represent the 55 strokes. The left bar of each pair represents the stroke length measured by the reference system, the right ones are the results of the new proposed method. © 2014 IEEE

3.7 Limitations

The system proved feasibility under the aforementioned circumstances. However, the authors are aware of limitations that can affect the system’s performance:
Unsmooth movements, for example when the rower accidentally touches the water, might lead to wrong reset events.

Very slow stroke rates lead to small gyro values and the slope might be too flat to detect catch points reliably.

Some technique drills such as rowing without feathering will make the finish reset point detection fail.

The system can capture qualitative trends, but the quantitative accuracy of the stroke length is erroneous due to sensor misalignment, sensor offset/drift and variable scale factors.

Results concerning the reliability or repeatability are preliminary because the study only involved one user.

3.8 Conclusion and Outlook

Stroke length serves as an important measure of the successful completion of the rowing cycle. We performed a single-user study to explore the feasibility of measuring stroke length with a smart phone. The phone is strapped to the oar and switched on, allowing the phone-implemented IMU to deliver acceleration, gyroscope and magnetic field measurements. Three methods are compared to calculate oar angles from the raw measurements. The Android-implemented strap-down algorithm was not usable; it delivers very inconsistent measurements even with very periodic movement patterns. The finish-resetting algorithm failed to represent different stroke lengths even though managed to segment the strokes reliably. The catch-resetting algorithm underestimated the absolute stroke lengths by an average of 7.64°, although relative changes in stroke lengths were represented consistently. Better quantitative measurements could be achieved by introducing calibration and misalignment correction algorithms. However, the focus of this paper was on achieving ease of usability and capability of detecting qualitative trends rather than attaining maximum accuracy.

The next step is to implement the latter algorithm in the smart phone app. This will allow the user to receive instant feedback and online calculations.
The system could also be extended by strapping additional phones to all of the oars in a crew boat. This way, not only individual parameters of single rowers are extracted, but also those of the whole crew, which enables features such as crew synchronicity to be measured as well. Furthermore, an additional phone attached to the boat can deliver information about boat run.

Acknowledgments

The authors thank all of the participants in the presented and previous pre-studies. Further thanks go to Rosa Brown (www.topproofreading.com) for proofreading this work.
Chapter 4  Oar Angle Measurement System Integrated In Rowing Oars

Franz Gravenhorst, Timothy Turner, Conny Draper, Richard M. Smith, Gerhard Tröster

Original publication title: Validation of a Rowing Oar Angle Measurement System based on an Inertial Measurement Unit

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Abstract

Measuring the horizontal rowing oar angle in an unobtrusive way is an unsolved problem for the rowing community and an interesting field for ubiquitous computing. We present the design and implementation of a new rowing oar angle measurement system that is based on an inertial measurement unit mounted inside the rowing oar and a user interface running on a waterproof smartphone. As well as proving the feasibility, we evaluate the accuracy of our system by comparing its performance with a more obtrusive system which is currently state-of-the-art. The mean deviation of the stroke length measurements between both systems is 1.81%.

4.1 Introduction

Rowing is one of the oldest Olympic disciplines and the number of participating athletes is increasing annually by 5% [12]. Rowing training can be divided into two parts, fitness and technique training. Learning the proper rowing technique is not only important for competitive athletes who aim to increase their boat speed, but also for social rowers to prevent injuries [15]. For technique training it is necessary to have a human coach who usually sits in a motor boat and follows the on-water training. Thus, the availability for coaching is limited and only accessible for a minor percentage of the rowing community. Technical tools for rowing technique analysis currently require extended setup time and are meant to be operated by experienced coaches.

4.1.1 Rowing Technique

To produce the power necessary to propel the boat, rowers must use all the major joints of the body. The rower is seated on a sliding seat facing the stern of the boat. The periodic rowing movement can be segmented into rowing strokes (see Figure 36). One rowing stroke consists of two phases, the drive phase and the recovery phase. At the beginning of the drive phase the rower’s elbow is extended while shoulder, spine, hip, knee and
ankle joints are flexed to attain maximum forward reach (Photo 3, Figure 36). At this position, the catch position, the blade enters the water. The rower then moves the blade through the water until the end of the drive phase, reaching the finish position (Photo 6, Figure 36). At this point, the elbow is flexed while the shoulder, spine, hip, knee and ankle are more extended. During the recovery the joint actions are reversed to bring the rower back to the posture at the beginning of the drive phase thus completing a cycle the rowing stroke. This is repeated around 250 times in the standard 2000 m race. Every stroke must be consistent with optimal technique to produce the best boat performance.

One important variable of optimal technique is the horizontal oar angle and its range of motion commonly referred to as the stroke length. The horizontal oar angle describes the movement of the blade in parallel to the water surface as illustrated in Figure 37.

Stroke length was considered to be one of the important determinants of rowing performance [99] and had a correlation coefficient of 0.76 (p < 0.001) with rowing speed during maximal rowing on an ergometer by elite rowers [54]. Horizontal oar movement has featured in real time augmented feedback to optimize mean boat velocity [80].
4.1.2 Related Work

Various research has been done to analyze rowing motions in dry setups, like rowing on ergometers [19, 58, 17] or on rowing simulators [103, 80]. Thanks to the miniaturization, more and more sensor devices can now also be fitted into rowing equipment and more measurements can be done in on-water setups. The most common electronic device used in rowing boats is the StrokeCoach device by NielsenKellermann [74]. The main purpose of the StrokeCoach is to measure the stroke rate by detecting the seat sliding intervals; this is achieved using a magnet and a reed switch. Schaffert et al. [85] sensorized a boat with accelerometers and converted the sensor measurements into sound, which was then played back to the athlete in real-time. Sinclair et al. [92] presented a setup for measuring the force applied to a rowing oar. The most common approach to measure the horizontal oar angle is based on wired potentiometers [71, 63].

The idea of using mobile inertial measurement units and ubiquitous computing for sports applications is mentioned in several patents [5] but only very few devices are already available for daily use in the sports community.

In previous work [43, 102, 44, 45] we researched several sensor modalities, which can be included in a boat area network to obtain meaningful data about rowing technique, this included measurements of the seat position with ultrasonic sensors and analysis of the boat movement with wired and
wireless inertial measurement units. In this work we propose and test the feasibility of an additional unobtrusive sensor node for measuring the horizontal oar angle which can be included in a boat area sensor network.

4.1.3 Contributions

In this work we aim to advance the state of the art in the following respects:

- Analysing and presenting the requirements for an ideal oar angle measurement sensor.
- Describing the system design of a wireless, easy-to-install and -operate oar angle measurement system that is based on an inertial measurement unit and a user interface running on a smartphone.
- Presenting a modified strapdown algorithm to calculate angles out of raw inertial sensor data when high dynamic movements are involved, such as rowing movements.
- Demonstrating the feasibility of our proposed hardware and software implementation in a proof-of-concept study.
- Evaluating the accuracy of horizontal angle measurements of our new system against a wired state-of-the-art potentiometer-based system.

4.1.4 Paper Organisation

Firstly, we provide an overview of the overall system design and then provide details about the developed hardware, the user interface and the software algorithm. In order to confirm the technical feasibility and accuracy of our system, we conducted a proof-of-concept study. We describe the experiment design and present our findings. Finally, we draw conclusions and give an outlook.
4.2 Rowing Oar Angle Measurement System

4.2.1 Requirements

In discussions with professional rowing coaches, biomechanics and rowing equipment manufacturers we identified the following requirements for an ideal rowing oar angle measurement system:

- **Useful.** The measured modality should be relevant for rowing and the accuracy should be reasonable. For the horizontal rowing angle an accuracy of two degrees is acceptable.

- **Mobile.** The system should be suitable for on-water usage, which implies that it is water-resistant, fits into a rowing shell and has a reasonable battery lifetime. Also, there should be no wires which limit the range of motion of the boat.

- **Unobtrusive.** The system should measure the natural rowing motion and ideally not affect or limit the rowing motion in any respect. The feeling for the athlete and the performance of the boat should ideally remain the same. This implies small form-factors, hidden mountings and light weights.

- **User-friendly.** The setup of the system should not require any non-reversible changes to the boat material and should be possible with reasonable training within less than 30 minutes. The user-interface to operate the system should be easy to access and understand.

- **Compliance with rules.** The changes that are required to be made to the rowing equipment must comply with the rules of the appropriate national rowing federation. To allow the usage within international rowing, the FISA (Fédération Internationale des Sociétés d’Aviron) rules of racing [35] apply.
4.2.2 System Overview

Our new system consists of an oar angle measurement board mounted in a waterproof enclosure which in turn is mounted inside the oar. The oar is modified with the addition of a waterproof battery charging port and power switch (see Figure 38).

Tri-axial MEMS sensors on the oar angle measurement board detect changes in the oar’s angular rotation rate, linear acceleration and magnetic field state.

The sensor data is transmitted via the Bluetooth protocol to the user interface application running on a waterproof mobile phone mounted with a suction cup holder on the rowing shell (see Figure 39).
4.2.3 Hardware Description

4.2.3.1 Mobile Phone as User Interface

An Android based mobile phone was used to run the user interface application. Android was chosen because of its Open Source nature and high market penetration [40], ensuring compatibility to a great diversity of mobile devices.

Also, since the mobile device to be used was to be subject to a large amount of water exposure, the IP57 rated Sony Xperia Acro S was selected. The key features are listed in Table 4.

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Sony</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Xperia Acro S</td>
</tr>
<tr>
<td>Waterproof</td>
<td>Yes, IP57</td>
</tr>
<tr>
<td>Size</td>
<td>126x66x12 mm³</td>
</tr>
<tr>
<td>Weight</td>
<td>147 g</td>
</tr>
<tr>
<td>Screen</td>
<td>4,3” Touchscreen</td>
</tr>
<tr>
<td>Connectivity</td>
<td>Bluetooth 3.0, 3G</td>
</tr>
<tr>
<td>Battery</td>
<td>Li-Ion, 1910mAh</td>
</tr>
<tr>
<td>Battery lifetime</td>
<td>&gt; 7h</td>
</tr>
<tr>
<td>Memory</td>
<td>16 GB, 1 GB RAM</td>
</tr>
</tbody>
</table>

Table 4: Key Features of Mobile Phone [7]. © 2013 IEEE

The user interface application implements the following tasks:

- **Connectivity.** The application establishes the connections to one or multiple sensor units via Bluetooth.
- **Synchronization.** If more than one sensor unit is used at the same time (left and right oar, or multiple rowers in a crew boat), the clocks of all devices are synchronized at start of data recording.
Oar Angle Measurement System Integrated In Rowing Oars

- **Interaction.** The touch screen provides an intuitive way of operating the measurement system, for example initializing the Bluetooth connection and controlling data recording.

- **Visualization and Feedback.** The received data is displayed on the phone’s screen in real time.

- **Internal Storage.** The application stores the received data to the local memory.

- **Cloud Storage.** After a test run, locally stored data is immediately copied to a user selected cloud web space so that it can be accessed in near real-time by a web-enabled workstation, notebook or tablet PC.

### 4.2.3.1 Oar Angle Measurement Unit

The oar angle measurement unit circuit board (see Figure 40) contains three tri-axial MEMS sensors. The InvenSense ITG-3200 [3] gyro measures angular rotation rate, the Bosch BMA180 [1] measures linear acceleration and the Honeywell HMC5883L [2] measures magnetic field state.

![Figure 40: Oar angle measurement unit circuit board showing Roving Networks RN-42 Bluetooth module (1), Bosch BMA180 acceleration sensor (2), InvenSense ITG-3200 gyro sensor (3), Honeywell HMC5883L magnetic field sensor (4) and Texas Instruments LM3S1968 MPU (5). © 2013 IEEE](image-url)
Data from the sensors are sampled at 100Hz via a Texas Instruments Stellaris LM3S1968 [4] Microcontroller which transmits the data via the Roving Networks RN-42 [6] Bluetooth module to the mobile device running the user interface application.

The oar angle measurement unit circuit board is mounted inside a waterproof enclosure that is mounted inside the oar. A waterproof battery charging port and switch is mounted in the oar handle. These are connected internally to the oar angle measurement unit via a waterproof connector. Thus the oar does not need to be disassembled for charging or normal operation. The overall specifications are listed in Table 5.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size w/o housing and battery</strong></td>
<td>105x25x10 mm³</td>
</tr>
<tr>
<td><strong>Size with housing and battery</strong></td>
<td>113x35x26 mm³</td>
</tr>
<tr>
<td><strong>Weight w/o housing and battery</strong></td>
<td>15 g</td>
</tr>
<tr>
<td><strong>Weight with housing and battery</strong></td>
<td>80 g</td>
</tr>
<tr>
<td><strong>Battery</strong></td>
<td>Li-Ion, 850mAh</td>
</tr>
<tr>
<td><strong>Sampling Frequency</strong></td>
<td>100Hz</td>
</tr>
<tr>
<td><strong>Battery lifetime</strong></td>
<td>&gt; 6h</td>
</tr>
</tbody>
</table>

Table 5: Specification of oar angle measurement unit. © 2013 IEEE

### 4.2.4 Angle Calculations with Inertial Measurement Units

#### 4.2.4.1 General Strapdown Algorithm

So-called strapdown algorithms are used to calculate orientation angles from raw sensor data. One common approach for mobile applications is based on Bachmann’s [21] complimentary filter which has recently been extended by Young [112]. It takes triaxial accelerometer, magnetometer and gyroscope data into account and consists of three steps, the orientation estimation, the integration and the fusing step as depicted in Figure 41.
Orientation Estimation Step. In this step, the accelerometer data $a$ and the magnetometer data $m$ is taken into account to estimate the absolute orientation of the sensor’s local inertial coordinate frame in respect of the global earth-fixed frame. Common approaches for this step are the TRIAD [67], FQA [111] or QUEST [90] algorithms. These algorithms assume the sensor does not perform any dynamic motion, which means the measured acceleration consists solely of the earth’s gravity.

Our implementation bases on the TRIAD algorithm and the resulting orientation is represented as column vectors of the rotation matrix $R_{est}$:

$$a_{norm} = \frac{a}{\|a\|}$$  \hspace{1cm} (1)

$$b = \frac{a_{norm} \times m}{\|a_{norm} \times m\|}$$  \hspace{1cm} (2)

$$c = b \times a_{norm}$$  \hspace{1cm} (3)

$$R_{est} = (c \mid b \mid a_{norm})$$  \hspace{1cm} (4)
Finally, the matrix $R_{est}$ is converted [88] to a quaternion $q_{est}$.

**Integration Step.** In this step, the orientation solution in quaternion representation $q_t$ from the previous time step and the angular rate data $\omega = (\omega_1, \omega_2, \omega_3)^T$ from the gyroscope sensor is used to calculate the new preliminary orientation $\tilde{q}_{t+1}$:

$$\tilde{q}_{t+1}^* = q_t + 0.5 \cdot T \cdot \text{mul} \begin{pmatrix} 0 \\ q_t \\ \omega_1 \\ \omega_2 \\ \omega_3 \end{pmatrix} \quad (5)$$

$$\tilde{q}_{t+1} = \frac{\tilde{q}_{t+1}^*}{\|\tilde{q}_{t+1}^*\|} \quad (6)$$

The function $\text{mul}$ is the quaternion multiplication [24].

**Fusion Step.** In this step, the quaternion from the estimation step $q_{est}$ and the quaternion from the integration step $\tilde{q}_{t+1}$ are merged together to get the final solution $q_{t+1}$:

$$q_{t+1}^* = \tilde{q}_{t+1} + \frac{1}{k} \cdot (q_{est} - \tilde{q}_{t+1}) \quad (7)$$

$$q_{t+1} = \frac{q_{t+1}^*}{\|q_{t+1}^*\|} \quad (8)$$

If the initial solution $q_{t=0}$ is unknown, it is estimated with an initial estimation step:

$$q_{t=0} = q_{est} \quad (9)$$

For visualization and interpretation purposes, the final quaternions are eventually converted [89] into triplets of Euler angles.

4.2.4.1 *Strapdown Algorithm for High Dynamic Motion*
As mentioned in the previous subchapter, the presented orientation estimation step assumes that the sensor system is not moving. The more dynamically the sensor is moved, the bigger the induced error in $q_{est}$ is, and the smaller the parameter $k$ is chosen, the more the final quaternion $q_{t+1}$ is influenced by this error.

In a pre-study we optimized the parameter $k$ for our rowing application, which revealed that the best orientation solution was obtained when the fusion step is skipped, which is equivalent to high values of $k$. This means that the orientation estimation step has to be performed only once, at the beginning of the experiment to obtain the initial orientation. As soon as the dynamic rowing movement starts, only the integration step is performed which means only the gyroscope data is used and has to be sampled from then on. The overview of the modified algorithm is depicted in Figure 42.

Figure 42: Overview of modified strapdown algorithm during high dynamic movements: Only the initial orientation estimation requires acceleration and magnetometer data. The following iteration steps are performed solely based on the gyroscope and previous quaternion data, the output is the new quaternion data. © 2013 IEEE

4.3 Experiment

To validate the accuracy of the horizontal rowing angle measurements (Figure 37) of our proposed IMU based system we benchmarked its performance against a reference system. The reference system we chose was a Peach Innovations measurement oarlock, a state-of-the-art wired potentiometer-based system, one of the most common systems used by professional rowing coaches and national rowing associations. According to the
manufacturer, the Peach system provides an accuracy of 0.5 degrees [71]. An overview about the reference system’s specifications is listed in Table 6.

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Peach Innovations Ltd.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product name</td>
<td>Instrumented Oarlock and Logger</td>
</tr>
<tr>
<td>Logger size with housing and battery</td>
<td>$103 \times 72 \times 30 \text{mm}^3$</td>
</tr>
<tr>
<td>Sampling Frequency</td>
<td>$50 \text{Hz}$</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.5 degrees</td>
</tr>
<tr>
<td>Connectivity</td>
<td>Wired</td>
</tr>
<tr>
<td>Storage Capacity</td>
<td>$&gt; 10 \text{h}$</td>
</tr>
<tr>
<td>Battery lifetime</td>
<td>$&gt; 4 \text{h}$</td>
</tr>
</tbody>
</table>

Table 6: Specification of reference system: Peach Innovations measurement oarlock [71]. © 2013 IEEE

We used a SYKES racing shell and instrumented it in a dry setup with a Peach Innovations measurement oarlock as shown in Figure 43. Oarlocks are part of every rowing boat, they hold the rowing oars and during the rowing movement they rotate with the oar, thus performing the same horizontal angular movement as the oars.

Figure 43: Instrumented oarlock as reference system: (1) shows the oarlock with the implemented potentiometer and (2) is the cable which runs from the oarlock to the logger unit which is mounted inside the boat shell. © 2013 IEEE
The measurement oarlock was installed according to the manufacturer’s guidelines, which involved substituting the ordinary oarlock with the instrumented one, attaching the Peach Innovations logger unit to the boat, wiring the system and performing calibration routines.

We prepared a CROKER racing oar with our new rowing angle measurement system and put this oar in the measurement oarlock. CROKER racing oars are one of the most common used rowing oars by Olympic level athletes. For our instrumented oars no calibration routines were required except to hold it still for a few seconds before we began with the dynamic movements. We started both systems, the instrumented oar and the instrumented oarlock and recorded 15 cycles of rowing with different stroke lengths and without feathering the blade. For documentation and annotation purposes, the procedure was video-taped with a high-definition camcorder.

### 4.4 Results and Discussion

We compared the horizontal rowing angles of our new IMU based system with the reference system in two ways, we compared it sample-by-sample and we compared the calculated stroke length, which is the most important feature coaches are interested in. An example of the acquired sensor data is shown in Figure 44.

#### 4.4.1 Sample-by-sample comparison

In a first step, the data from the IMU based system was down sampled from 100Hz to 50Hz, to match with the reference system’s sample rate and to allow a sample-by-sample comparison. The two data streams from both sensor systems were aligned manually. Then the continuous data stream was segmented automatically into strokes by applying a peak detection algorithm [102].
For each stroke, we calculated the correlation coefficient $R$:

$$R = \frac{\sum_{i=1}^{N} (imu(i) \cdot ref(i))}{\sqrt{\sum_{i=1}^{N} (imu(i)^2) \cdot \sum_{i=1}^{N} (ref(i)^2)}}$$  \hspace{1cm} (10)$$

where $imu(i)$ and $ref(i)$ with $i = 1..N$ are the horizontal angle samples of the considered stroke acquired by our proposed IMU based system and the reference system respectively.

Also, for each sample $i$ within the considered stroke the deviation between the two systems was calculated as error $e(i)$:

$$e(i) = |imu(i) - ref(i)|$$  \hspace{1cm} (11)$$
For each stroke the mean, the standard deviation and the maximum of this error is calculated. The results are summarized in Table 7. Considering all strokes the average correlation coefficient is

$$\bar{R} = 0.9989 \pm 0.0005$$

and the average mean error is

$$\bar{\epsilon} = 1.27^\circ \pm 0.40^\circ$$

<table>
<thead>
<tr>
<th>Stroke #</th>
<th>R</th>
<th>Mean Error [°]</th>
<th>Std Error [°]</th>
<th>Max Error [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9996</td>
<td>0.83</td>
<td>0.63</td>
<td>2.06</td>
</tr>
<tr>
<td>2</td>
<td>0.9995</td>
<td>0.94</td>
<td>0.46</td>
<td>1.78</td>
</tr>
<tr>
<td>3</td>
<td>0.9995</td>
<td>0.92</td>
<td>0.47</td>
<td>1.80</td>
</tr>
<tr>
<td>4</td>
<td>0.9994</td>
<td>1.02</td>
<td>0.48</td>
<td>1.73</td>
</tr>
<tr>
<td>5</td>
<td>0.9994</td>
<td>0.94</td>
<td>0.46</td>
<td>1.90</td>
</tr>
<tr>
<td>6</td>
<td>0.9993</td>
<td>0.89</td>
<td>0.53</td>
<td>2.03</td>
</tr>
<tr>
<td>7</td>
<td>0.9986</td>
<td>0.70</td>
<td>0.63</td>
<td>2.33</td>
</tr>
<tr>
<td>8</td>
<td>0.9984</td>
<td>1.54</td>
<td>1.24</td>
<td>3.61</td>
</tr>
<tr>
<td>9</td>
<td>0.9985</td>
<td>1.57</td>
<td>1.14</td>
<td>3.28</td>
</tr>
<tr>
<td>10</td>
<td>0.9989</td>
<td>1.40</td>
<td>1.07</td>
<td>3.28</td>
</tr>
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<td>11</td>
<td>0.9988</td>
<td>1.42</td>
<td>1.20</td>
<td>3.47</td>
</tr>
<tr>
<td>12</td>
<td>0.9987</td>
<td>1.66</td>
<td>1.15</td>
<td>3.95</td>
</tr>
<tr>
<td>13</td>
<td>0.9979</td>
<td>2.02</td>
<td>1.52</td>
<td>4.82</td>
</tr>
<tr>
<td>14</td>
<td>0.9989</td>
<td>1.49</td>
<td>1.11</td>
<td>3.64</td>
</tr>
<tr>
<td>15</td>
<td>0.9985</td>
<td>1.71</td>
<td>1.35</td>
<td>4.09</td>
</tr>
</tbody>
</table>

Table 7: Results of sample-by-sample comparison of the horizontal rowing oar angle measurements of our IMU based approach with a potentiometer-based reference system: For each stroke the calculated correlation coefficient R, the mean error, the standard deviation of the error and the maximum error of the measurements are listed. © 2013 IEEE
4.4.2 Stroke length comparison

As proposed by Tessendorf et al. [102] we calculated the stroke length as the peak-to-peak amplitude of the horizontal rowing angle measurements. The calculated stroke lengths from all strokes are listed in Table 8. The deviation between our IMU based system and the reference system is recognized as error.

<table>
<thead>
<tr>
<th>Stroke #</th>
<th>Length Reference [°]</th>
<th>Length IMU [°]</th>
<th>Error [°]</th>
<th>Error [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>85.06</td>
<td>86.09</td>
<td>1.03</td>
<td>1.21</td>
</tr>
<tr>
<td>2</td>
<td>85.00</td>
<td>86.41</td>
<td>1.41</td>
<td>1.66</td>
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<td>80.16</td>
<td>0.91</td>
<td>1.15</td>
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<td>4</td>
<td>80.50</td>
<td>81.81</td>
<td>1.31</td>
<td>1.62</td>
</tr>
<tr>
<td>5</td>
<td>81.50</td>
<td>82.51</td>
<td>1.01</td>
<td>1.24</td>
</tr>
<tr>
<td>6</td>
<td>77.44</td>
<td>78.08</td>
<td>0.64</td>
<td>0.83</td>
</tr>
<tr>
<td>7</td>
<td>47.88</td>
<td>49.79</td>
<td>1.91</td>
<td>4.00</td>
</tr>
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<td>99.30</td>
<td>2.30</td>
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</tr>
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<td>2.10</td>
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<td>106.19</td>
<td>1.25</td>
<td>1.19</td>
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<tr>
<td>11</td>
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<td>103.02</td>
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<tr>
<td>15</td>
<td>101.06</td>
<td>103.12</td>
<td>2.06</td>
<td>2.04</td>
</tr>
</tbody>
</table>

Table 8: Stroke length measurements, comparison of our IMU based approach with potentiometer-based reference system. © 2013 IEEE

Considering all strokes the average error of the stroke lengths is

\[ \overline{e_{\text{length,abs}}} = 1.56° ± 0.63° \]

\[ \overline{e_{\text{length,rel}}} = 1.81\% ± 0.86\% \]
4.5 Conclusion and Outlook

4.5.1 Conclusion

In collaboration with rowing coaches, biomechanics and rowing equipment manufacturers we identified the requirements for an ideal rowing oar angle measurement system. Based on these findings we designed a new system which is based on an inertial measurement unit and a user interface running on a waterproof smartphone. We describe the hardware and software implementation to derive the horizontal angle measurements. The feasibility of our proposed system is shown by a proof-of-concept study. Finally, we evaluated the accuracy of our new contactless and wireless system against a wired state-of-the-art potentiometer-based system. The measurements of both systems were quite similar, the correlation coefficient was 0.9989±0.0005. Considering the potentiometer-based system as a gold standard, the stroke length measurements of our new contactless approach showed errors of 1.56°±0.63°.

4.5.2 Limitations

We are aware that our proposed system and its evaluation involve several limitations:

- We tried to meet most of the requirements mentioned in section 4.2.1 to come as close to an ideal system as possible. While our system meets many of our targets, it still falls short of our goals in some areas. For example, in relation to the unobtrusiveness criterion rowers may be concerned that the additional weight of a smart phone is too much to carry during a race and interaction with a phone during rowing may be too distracting.

- To estimate the accuracy of our new system we assume that the potentiometer-based reference system obtains reliable and accurate measurements.
• The horizontal rotation of the measurement oarlock does not necessarily match ideally with the horizontal rotation of the oar because the oar is not fixed tightly inside the oarlock. That is also an explanation as to why the mismatch between both measurements is particularly high at the turning points of the movement.

• In this study we only evaluated the horizontal oar angle, since our reference system was only capable of measuring the angle in this particular dimension. Thus, in this experiment the blade was not feathered as it would normally have been in normal rowing.

• The proposed modified strapdown algorithm involves an error for long-term measurements as the absolute position is only set once at the start of the recording. However, for rowing technique analysis, coaches are often interested in recording only a few strokes and analyse them in detail.

4.5.3 Outlook

We plan to combine the presented rowing oar angle measurement system with other sensors such as a force measurement system, which is also to be integrated seamlessly inside the oar. With this system, coaches could not only investigate the trajectory of the oar angles, but also the force distribution over a stroke. The system is already ready to be applied in crew boats to monitor the crew’s synchronicity in terms of moving the oars parallel to each other. The usability and validation of this feature is subject to further studies.

Our vision is to build a boat area network with a set of unobtrusive sensor nodes which enables real-time feedback for the coaches and athletes and that is practical for daily use.

The presented proof-of-concept study is a first step towards this vision. Our system has the potential in offering comparable data as state-of-the-art systems with at the same time being less obtrusive and faster to install. The
continuing miniaturization and availability of inertial measurement units for wearable computing are contributing to meeting the requirements of sports applications. We believe that bridging the boundaries of ubiquitous computing and sports science can further develop the sports.

Acknowledgments

The authors would like to thank Rosa Brown, University of Sydney, for contributing helpful ideas and language skills and Steve Luker, Head Coach at UTS Rowing Club, Australia, for lending boats and facility use. Further thanks go to all participants in the studies and pre-studies, and the collaborating coaches for their feedback.
Chapter 5   Rowing Seat Position Measurements Based on Accelerometers and Magnetometers

Franz Gravenhorst, Christoph Thiem, Bernd Tessendorf, Rolf Adelsberger, Christina Strohrmann, Bert Arnrich, and Gerhard Tröster

Original publication title: Self-Aligning and Drift-Compensated Rowing Seat Position Measurement System Based on Accelerometers and Magnetometers

9th Symposium Sportinformatik, 2012

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5.1 Introduction and Related Work

The rowing motion is a complex sequence of limb movements. In order to improve the boat speed as well as to prevent injuries, athletes and coaches are interested in analyzing and optimizing it in an objective and reliable way. In previous work, we implemented a sensor network to measure the oar movement and the boat stability [102, 44, 45]. In this work we focus on extending our system with a position tracker of the sliding seat.

The movement of the sliding seat is directly linked to the rower’s leg movement which involves the rowers’ most powerful muscles and thus is a key element in rowing technique. Bad technique in the leg movement significantly slows down the boat speed and can result in injuries. The most commonly used system to monitor the sliding seat movement nowadays is the commercial StrokeCoach™ device by Nielsen Kellerman [74]. This system consists of a permanent magnet attached to the sliding seat and a reed switch fixed to the boat. This way, it measures the stroke rate (how often the rower moves the seat back and forth per minute) but there is no information about the shape of the motion. Another approach is presented by Kleshnev [63] and Smith et al. [96]. They attach a cord to the sliding seat which drives a potentiometer when the seat moves. These measurements are proven to be helpful for coaches. However, the installation and calibration requires some effort and elite rowers report unnatural feelings as the cord constantly pulls the seat to one direction. An approach based on optical methods is presented by Davoodi et al. [33]. They employed the system and obtained reasonable results for indoor rowing. However, it is not yet ready for on-water environments.

5.2 Contribution

We present a seat position tracker system which consists of two miniaturized measurement units attached to the sliding seat and the boat shell. Each unit features a tri-axial accelerometer and magnetometer. We present a method how to process the raw data to calculate the seat position. The magnetometer data is used to correct for low-frequency sensor drift.
Three accelerometer axes and prior knowledge concerning the boat geometry is exploited to feature a dynamic calibration algorithm, which corrects for misalignments between the two mounted sensor nodes.

We implemented a first version of the devised system and performed a proof-of-concept data recording on the water.

5.3 Seat Position Tracking System

5.3.1 Requirements

In collaboration with elite rowers and coaches we found that besides delivering accurate and continuous measurements, unobtrusiveness is a main requirement for an ideal seat position tracking system. The rower should be able to row and feel as usual and not being disturbed or distracted by the system. This implies a small form factor, and a light weight and contactless measurement approach.

5.3.2 Hardware Setup

As measurement devices we used two ETHOS modules [51, 101]. ETHOS modules (Figure 45c) are small (WxLxH: 48x61x8 mm, including housing and battery) and lightweight (22g) inertial measurement units (IMUs). Besides recording angular velocities, they measure accelerations (static accuracy: 0.2-3.2mg [51]), and magnet fields (static accuracy: 2mGa [51]), each in all three dimensions. The data was sampled at 128Hz and stored to a local non-volatile memory. Thanks to the included Li-Ion battery and the internal memory, there was no persistent wiring needed, neither for power supply nor for data transmission during measurements.

One ETHOS module was fixed to the bottom side of the sliding seat and the other one was attached to the boat shell between both tracks of the seat (Figure 45). Additionally, a permanent magnet was attached close to the seat sensor. A reed contact was placed close to the second sensor module and wired to this module. Both of these devices, permanent magnet and
reed contact, are also components of *Nielsen Kellerman’s StrokeCoach™* system which is a very popular rowing accessory and thus already off-the-shelf installed in almost all elite level racing boats. In this case, only an additional wire from the reed contact to the ETHOS module is necessary.

5.3.3 Sensor Node Synchronization

As the two sensor modules are not wired together during the measurement, they have two individual clocks which need to be synchronized. We implemented an application for Android mobile phones which sends a synchronization signal to both ETHOS devices. This communication follows the low-energy wireless ANT+ protocol [8]. This procedure has to be done only once after the ETHOS devices are powered.

5.3.4 Seat Position Calculation Overview

It is assumed that the x-axes of both sensor modules are approximately aligned to the direction of the intended boat movement. It turns out that slight misalignments of both sensor modules relatively to each other are in particular critical whereas the effect of slight misalignments of a sensor module relatively to the boat axes is negligible.

The calculation of the seat position consists of several steps: Firstly, the alignment of the two employed sensor units relatively to each other is identified. The sensor values are corrected for this misalignment. Then, the acceleration of the seat relatively to the boat is calculated. These values are corrected for drift errors and finally a double integration leads to the seat position.

These steps are described in detail in the following paragraphs.
Figure 45: Acceleration based sliding seat position tracker (b) mounted in a rowing boat (a). The core units are two synchronized tri-axial acceleration sensors: one of them is attached to the bottom of the sliding seat (2) and the other sensor module is fixed to the boat shell (3). For drift compensation, the system is supplemented with a permanent magnet (1) attached to the seat and a reed switch (4) attached to the boat and wired to the sensor module (3). The used ETHOS sensor module is shown in (c).
5.3.5 Identification of Sensor Orientation for Dynamic Self-Alignment

The sensor which is attached to the seat measures the superposition of the acceleration of the boat relatively to the ground and the acceleration of the seat relatively to the boat. The sensor attached to the boat only measures the acceleration of the boat relatively to the ground. To derive the seat position relatively to the boat we have to calculate the seat acceleration relatively to the boat, this is the difference between the acceleration vectors of the two sensors. However, we have to take into account that these sensors are usually not perfectly aligned to each other and thus their coordinate systems are different. To correct for this misalignment, the values of one sensor have to be adjusted by multiplying them with a rotation matrix [108]:

$$
(\vec{acc}_x, \vec{acc}_y, \vec{acc}_z)^T(n) = \vec{acc}(n) = \text{rot}(\phi, \theta, \psi) \cdot \vec{acc}_{\text{seat}}(n) - \vec{acc}_{\text{boat}}(n)
$$

(12)

This rotation matrix $\text{rot}(\phi, \theta, \psi)$ depends on three Euler angles $\phi$, $\theta$ and $\psi$, which describe the misalignment between the coordinate systems of the two sensor nodes. We used Kirkpatrick’s Simulated Annealing optimization algorithm [59] to identify these angles. We exploited the knowledge that due to its fixed tracks, the sliding seat’s movement relative to the boat can only be one-dimensional (x-axis). Thus, after finding the optimal values for the Euler angles the resulting acceleration vector $\vec{acc}(n)$ should have negligible values in its components $\vec{acc}_y$ and $\vec{acc}_z$. The optimization criterion for the algorithm was:

$$
cost = \sum_n |\vec{acc}_y(n)| + |\vec{acc}_z(n)|
$$

(13)

This algorithm enables the dynamical identification of the sensor misalignment based on rowing movements. No static calibration procedure is necessary.
5.3.6 Drift Compensated Seat Position Calculation

The seat position $h(n)$ can basically be derived by a double integration of the acceleration component $acc_x(n)$. However, due to non-ideal sensor characteristics we have to take a low-frequency sensor drift $acc_{err,i}$ into account which is the difference between the measured acceleration $acc_x(n)$ and the actual acceleration $acc_{real}(n)$:

$$acc_x(n) = acc_{real}(n) + acc_{err,i}$$  \hspace{1cm} (14)

We assume the sensor drift $acc_{err,i}$ to be constant during one cycle of a rowing stroke. Thanks to the reed switch at the tracks of the sliding seat, we record the points in time when the sliding seat with the attached permanent magnet passes the reed switch. Every other passing $n_i$ means that another full stroke is finished.

By exploiting the knowledge that for all these points in time $n_i$ the seat position $h(n_i)$ is the same

$$h(n_i) = h(n_j) \quad \forall i, j$$  \hspace{1cm} (15)

we can calculate the appropriate values for the sensor drift $acc_{err,i}$ for every stroke $i$ and then calculate the drift-corrected seat positions $h(n)$.

As an alternative to the reed switch, the strokes can also be segmented by the magnetic field data which is also recorded by our sensor modules. The magnetic field peaks each time the permanent magnet passes the sensor at the tracks.

The effect of our drift-compensation algorithm is shown in Figure 46. This data has been recorded with an advanced rower during an on-water training session.
5.4 Limitations

Although we are convinced that our system is useful for measuring the seat position in rowing boats, there are still some limitations. The most obvious drawback might be the obtrusiveness – as our approach still requires the mounting of additional weight to the boat (magnet switch, reed switch, two ETHOS modules). However, the total additional weight is less than 100g and therefore less than what is necessary in all other alternative approaches we are aware of. Another limitation is the limited amount of parameters we are recording. Our approach only takes into account the sliding seat movement. Although, this aspect is of great interest for the rowing community, there are additional parameters of interest that are not yet covered by our system such as the upper body and hand movements. We are in the progress to extend the system accordingly.
5.5 Conclusion and Outlook

We presented a seat position tracker system which consists of two miniaturized IMUs attached to the sliding seat and the boat shell. We introduced a method how to process the raw data from the IMU to calculate the seat position. It corrects for low-frequency sensor drift, which allows the use of miniaturized low-cost sensors. Additionally, it features a dynamic calibration algorithm, which identifies the misalignment between the two sensor nodes without any dedicated calibration movements or need to attach the sensors in an accurately well-defined position or angle. Both features contribute to the system’s measurement accuracy and usability. We describe the implementation of a first version of the devised system and performed a proof-of-concept data recording on the water.

In the future we will combine this new modality to our existing rowing boat sensor network and perform measurements in on-water environments.
Chapter 6 Analyzing Rowing Boats based on Angular Velocity Measurements with Gyroscopes

Franz Gravenhorst, Bernd Tessendorf, Bert Arnrich, Camille Codoni, Gerhard Tröster

Original publication title: Analyzing Rowing Crews in Different Rowing Boats based on Angular Velocity Measurements with Gyroscopes

8th International Symposium on Computer Science in Sport, 2011

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Abstract

The overall performance in rowing competitions depends on crew-based parameters like technique and physical strength, environmental conditions like water temperature and wind, and material like the shape and the settings of the rowing boat. The market offers a broad variety of rowing boats. However, there is still no standardized test procedure which enables an objective comparison of different rowing boats and boat settings for a given crew. In this work we are proposing three performance metrics which can be used to compare the fitness of different boats, i.e. its stability in a quantitative way. The metrics are based on angular velocity measurements which can be obtained by gyroscopes, which usually come as a part of inertial measurement units (IMUs). In collaboration with national rowing team coaches we equipped two rowing boats of world level athletes with miniaturized IMUs. Based on the collected data we benchmarked the boats in respect of their stability for the given crew.

6.1 Introduction

Rowing is one of the oldest Olympic disciplines. The goal in rowing competitions is to move the boat as fast as possible from start to finish. Depending on the boat category, a usual race takes about 6-7 minutes, whereas fractions of a second may decide on the victory. The overall performance depends on crew-based parameters like technique and physical strength, environmental conditions like water temperature and wind, and material like the shape, weight and the settings of the rowing boat.

Most of the rowing related studies, which can be found in literature, are focusing on crew-based parameters, namely the analysis and possible improvements of the rowing technique of individual rowers. Typical approaches either base on some pieces of hardware which is to be carried within the boat [63, 85, 45] or they are restricted to users of indoor rowing machines [19, 17, 58] or rowing simulators [103].

Concerning the used material, there are still no standardized test procedures which allow the evaluation and optimization of rowing boats [37].
Moreover, the regulations which apply for all international rowing events, the FISA Rules of Racing [35] assure: “The construction, design and dimensions of boats and oars shall, in principle, be unrestricted [...]” (Rule 33). This contributes to a market offering a broad variety of rowing boats that allow adjusting many different mechanical settings like the position of the oarlock and the stretcher. It is a challenging task to select the optimal rowing boat and to optimize its settings for the individual characteristics of a given crew.

To tackle this issue, most coaches rely on their own subjective feelings or on subjective feedback they may receive from crew members [37]. Common technical tools are usually high speed cameras or stopwatches. Cameras enable the coaches to have a close look at the boat’s movement. However, with this method only qualitative analysis is possible and conclusions depend on the coach’s experience. Stopwatches can be used to compare the overall time a given crew scores for a given race distance in different boats. However, this approach assumes the very same conditions for both test races in several respects. This includes the same physical, psychological and technical strength of the crew, the same calm water surface and current, and the same wind and temperature conditions. Results show that experienced Olympic level crews, who race several times in the same boat under changing environmental conditions, achieve finish times which vary by more than 10 seconds [9].

In this study we are focusing on comparing the behaviour of different rowing boats in a quantitative way using novel ETHOS modules [51]. These sensor modules include a three-axis gyroscope which enables measuring the angular velocity of the boat movements. In collaboration with national rowing team coaches we propose a first step towards performance metrics that are relevant to compare the stability of different rowing boats for a given crew (chapter 6.2). We have equipped two rowing boats of world level athletes with these sensors (chapter 6.3), analysed the obtained data (chapter 6.4) to draw conclusions (chapter 6.5).
6.2 Performance Metrics

It is a challenging task to decide which boat fits best to a given crew. It depends on many parameters and due to the complex influence of these parameters this question cannot be answered in a reliable way by measuring overall finish times with a stopwatch. The same applies to other variants of measuring the average boat velocity, like GPS systems.

According to [15, 37] the stability and straightness of the boat movement is crucial for the resulting boat’s performance. Any variations to the boat’s expected main moving direction lead to increasing drag forces and a loss of energy [92]. The possible three turning directions are illustrated in Figure 47.

The reasons for unintended deviations in the moving directions can be manifold: The rower’s technique, weather, the boat’s shape and the boat settings. In this study, the measurements were done with the same crew, rowing subsequently in two different boats. As both measurements were done directly one after the other, the rower’s technical skills is assumed not to vary for both boats. Also, the overall weather conditions like temperature and wind direction are considered stable for these measurements.

Frequent changes in the boat’s orientation angles indicate a lack of stability. Changes in angles are quantified as angular velocities [105] and calculated according to equation (1), where $\Delta \alpha$ is the amount the angle $\alpha$ changes within the time interval $\Delta t$ :

\[ \Delta \alpha(t) = \frac{\alpha(t+\Delta t) - \alpha(t)}{\Delta t} \]
\[ \omega = \frac{\Delta \alpha}{\Delta t} \]  

Thus, the angular velocity is a reasonable measure for comparing the stability of different boats. To overcome arbitrary local influence like wavy water surface, we do not base the comparison of angular velocities on single strokes. Precisely, in this study, we consider a time interval of 10 strokes and computed the average amplitude, standard deviation and the range (maximum minus minimum) of the angular velocity. This is done separately for each of the three axes of the gyroscope.

6.3 Experiment

To record the sensed boat data we used ETHOS modules [51, 101]. ETHOS modules (Figure 48) are very small (WxLxH: 48x61x8 mm, including housing) and lightweight (22g) inertial measurement units (IMUs). Besides recording angular velocities with gyroscopes (static accuracy: 1°/s [51]), it measures accelerations and magnet field data, each in all three dimensions. The data is sampled at 128Hz and stored to a local non-volatile memory. Thus, no wiring is needed and the sensor can be attached unobtrusively to the oar or the boat.

![Figure 48: ETHOS module](image)

The main ETHOS module is mounted inside the boat. Additionally, a high speed video camera is used for visualisation tasks and a second ETHOS
module is mounted on one of the oars for easier segmentation of the recorded data. The complete experiment setup is shown in Figure 49.

![Experiment setup: a) High speed video camera b) ETHOS module on oar c) ETHOS module inside boat](image)

In collaboration with national rowing team coaches we selected an experienced rowing crew (U23 World Championships 2011, bronze medal winner) for our experiment. The crew rowed in two boats, boat A (length: 11.35m, width: 38cm, weight: 52kg) and boat B (length: 11.78m, width: 40cm, weight: 52kg), of different manufacturers. The settings of each boat were adjusted analogically to fit best to the crew’s requirements. The crew had rowed in both boats before, they were slightly more experienced in boat B. At the test day, the crew went out in boat A first and performed a programme which included warming-up and some test races over a 1.000m distance with given stroke rates. After that, the crew had a one-hour break. Subsequently, they performed an analogical procedure with boat B. In each boat the data was recorded according to the described setup (Figure 49). The same oars were used for both boats.

6.4 Results

An example of the measured signals is shown in Figure 50. It comprises three complete strokes. The label $T_1$ marks the end of a stroke, just when the blade leaves the water. $T_2$ marks the beginning of the next stroke, just before the blade goes into the water. Between these two time frames,
during the so-called recovery phase, the crew use their sliding seats to move their bodies from bow to stern to prepare for the next stroke. Due to this crew movement, a considerable amount of mass moves to the stern and causes a pitching movement of the boat. This increase of the pitching angle is represented by a positive pitch angular velocity in Figure 50 (solid line between $T_1$ and $T_2$).

The average amplitude, standard deviation and the range of the angular velocity have been computed for each of the three axes and for each of the two boats as described in section 6.2. Table 9 shows values for the pitch angular velocities for both boats.

<table>
<thead>
<tr>
<th></th>
<th>Average Amplitude</th>
<th>Standard deviation</th>
<th>Signal Range (Max-Min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boat A</td>
<td>0.0102</td>
<td>0.0124</td>
<td>0.0634</td>
</tr>
<tr>
<td>Boat B</td>
<td>0.0164</td>
<td>0.0215</td>
<td>0.2563</td>
</tr>
</tbody>
</table>

Table 9: Values of pitch angular velocity features for boat A and boat B in [rad/s]

In this example, all three performance metrics of the pitch angular velocity of boat A are smaller than the corresponding ones of boat B. In fact, this is also true for the performance metrics of the roll and yaw angular velocities. Also, the overall finish times for the test races were recorded manually by a stopwatch. In average, the crew finished in boat A 7 seconds faster than in
boat B. However, this was also influenced by a change of wind conditions on parts of the course. These parts were not taken into account for the calculation of the performance metrics.

6.5 Conclusion and Future Work

According to literature the stability of rowing boats is a key feature for their performance. We proposed performance metrics which base on angular velocities and quantify some aspects of boat’s stability. An experiment was conducted to compare the boat’s stability of two boats. The analysis of the computed performance metrics indicates that boat A is more stable than boat B. Manual stopwatch measures confirm that boat A moved faster than boat B.

However, one has to keep in mind that these results still rely on the assumption that the environmental conditions do not change significantly during the whole experiment. Further results have shown that the proposed performance metrics show significant correlation with the stroke rate. Sticking accurately to a given stroke rate is a challenging task even for advanced rowers.

In future work we want to reveal the influence of specific boat settings and the crew’s stroke rate on the boat’s stability. Also, additional metrics based on the boat’s acceleration are investigated. Finally, after recording larger data sets with more runs per crew we will be able to quantify the variations of our measurements and metrics.

Acknowledgments

The authors gratefully thank all the athletes participating in the study and the Swiss Rowing Federation, namely national coach Tim Foster, for collaboration.
Chapter 7 Oar Angle Measurements with IMUs Attached to the Oar

Bernd Tessendorf, Franz Gravenhorst, Bert Arnrich, Gerhard Tröster

Original publication title: An IMU-based Sensor Network to Continuously Monitor Rowing Technique on the Water

7th IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2011

© 2011 IEEE.
The final publication is available at http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6146535
Abstract

In the sport of rowing athletes and coaches are concerned with optimizing a rower’s technique in order to improve rowing performance. In this paper, we present the design and real-world evaluation of a sensor network approach to support improving the rower’s performance. In cooperation with professional rowing teams, we found that a network of inertial measurement units (IMUs) is well suited to continuously and unobtrusively monitor important indicators relating to rowing technique. In a feasibility study with 5 participants we first investigated the optimal sensor setup, and in the final setup we attached 3 IMUs to the oars and the boat. From 18 participants (including both ambitious amateurs and world-class rowers) we recorded both training and racing sessions which each consisted of 1000m rowing. We present 4 rowing technique indicators for all 18 participants. Using the example of two world-class rowers we demonstrate in detail how sensor networks support the iterative process of optimizing the individual rowing technique.

7.1 Introduction

The objective in a rowing race is to move the boat as fast as possible from the start to the finish. Besides their physical and mental strength, the rower’s technique is a key feature leading to success. In this paper, we investigate how to beneficially integrate inertial measurement units (IMUs) into the iterative process of optimizing rowing technique that is illustrated in the upper part of Figure 51. We address the following research questions: 1) Measurability: Can we use IMU data to quantify and visualize important rowing technique indicators such as stroke length and rhythm? (2) Accuracy: Is the system accurate enough to analyse the rowing technique and provide benefits for the optimization of rowing technique? (3) Practicality: Can we devise a robust system for daily use in “real life” which is sufficiently unobtrusive to not impair the rower when rowing?

The paper is structured as follows: In section 7.2 we describe the process of improving rowing technique, related work and a novel approach to support
this process. In section 7.3 we present the implementation of this approach using a sensor network and dedicated algorithms. In section 7.4 we describe the results for our proposed system in a real-world application and conclude in section 7.5.

Figure 51: The iterative process to optimize a rower’s technique: The standard approach and extension using a sensor network approach. © 2011 IEEE

7.2 Theory

7.2.1 Rowing Technique Basics

The basic rowing technique is illustrated in Figure 52. Rowing is a periodic movement. One cycle of rowing is explained in the following. The numbers given in brackets refer to the pictures in Figure 52. During the catch phase (1, 2) the oar blades are placed in the water. The catch is a quick accurate hand movement and should happen as early as possible to maximize the stroke length [35]. In crew boats (more than one rower in a boat) it is essential that all rowers perform the catch at the same time. In the drive phase (3) the legs are extended and then the body opens up (4), levering the boat forwards. The arms are straight and the lower back is firm. In the finish (5) the oars come out of the water and are feathered parallel to the water surface to minimize air resistance. In the recovery phase (6) the rower’s limbs move towards the stern in preparation for the next stroke: first the arms, then the upper body and finally the legs.
7.2.2 Improving Rowing Technique

Performance in rowing is measured with a recorded time from start to finish of a race. There are qualitative rowing technique guidelines from national and international rowing associations to explain why the time was achieved and how to improve it [37, 35, 15]. Table 10 lists a subset of these pieces of best-practice advice that allow further in-depth analysis of rowing technique. Key aspects include stroke efficiency, rhythm, timing, and boat stability. There are quantitative (e.g. velocity, stroke count) and qualitative (e.g. smoothness of movement) measures, but there is a strong need for both rowers and coaches to get more quantitative measures.

According to the FISA\(^1\) the long-term objective for the athlete is to master the rowing technique [35]. The goal is to maximize propulsion in the drive phase and to minimize the loss of speed due to friction during the recovery phase. To improve the rower’s technique the coach needs to identify the necessary changes in the movement. This is a challenging task because even small changes in rowing technique can significantly affect the finish of a race. Moreover, any fine-tuning and beneficial changes to rowing tech-

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\(^1\) The Fédération Internationale des Sociétés d’Aviron (FISA) is the international rowing federation.
nique are specific to the particular rower’s anatomy and rowing style and therefore have to be found for each rower individually. An analysis Olympic rowing champions confirms that many different kinds of technique lead to success [15].

<table>
<thead>
<tr>
<th>Rowing Technique Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consisted pattern and length</td>
<td>Each stroke should resemble the previous one (constant timing). The rower should stick to a long stroke length, even with high stroke rates like during racing conditions.</td>
</tr>
<tr>
<td>Good blade depth</td>
<td>To avoid losses but to maximize acceleration, the blade should not be too deep or too little in the water during the drive phase. Ideally, the deepness is equal to the blade’s height, so the upper edge is just covered with water. During the recovery phase there should be a gap between blade and water approximately as high as the blades’ width.</td>
</tr>
<tr>
<td>Firm, direct and consistent action of the blade</td>
<td>The blade should go into the water immediately after the most forward position (catch position) is reached. At the end of the stroke, the hands and the upper body should start moving towards the catch position without delay. The squaring of the blade should be early enough to be prepared for the catch.</td>
</tr>
<tr>
<td>Relaxed, but controlled body movement during the recovery</td>
<td>The horizontal moving velocity of the blade during the recovery phase should be constant without impulsive accelerations.</td>
</tr>
<tr>
<td>Powerful, smooth body movement</td>
<td>Smooth movement of the boat, jerky peaks in the acceleration curve should be avoided.</td>
</tr>
<tr>
<td>Synchronicity in crew boats</td>
<td>All members of a crew should perform the movements with exactly identical timing.</td>
</tr>
</tbody>
</table>

Table 10: Subset of rowing technique indicators advised by international and national rowing associations [37, 35, 15]. © 2011 IEEE

In our discussion with professional coaches we found that an iterative trial and error approach is used to optimize the rower’s technique as illustrated in the upper part of Figure 51. To assess the performance and to identify improvement opportunities the coach observes the rower’s technique and
also takes into account feedback from the athlete. The rower then attempts to make the changes in rowing technique suggested by the coach and the next iteration starts. This approach’s success depends on the experience of the coach, who needs to identify shortcomings and suggest appropriate steps based on their own personal qualitative observations. Therefore, novel approaches, which provide additional information to support the coach in this process are highly appreciated.

7.2.3 Related Work

On-board computers can provide the rower with the current stroke rate and split times related to speed over the distance covered. However, they don’t give any additional feedback on the parameters related to the rower’s technique. Visual feedback can be provided by video-goggles [11]. These are worn on the rower’s head and display the video signal as it is captured by an accompanying coach. In [85] the authors investigate sonification of boat acceleration as feedback to support synchronization in crew boats. Table 11 gives an overview of sensing approaches to collect data from rowing boats.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnet</td>
<td>Seat</td>
<td>Reed switch to count strokes</td>
</tr>
<tr>
<td>Spirit level</td>
<td>Boat</td>
<td>Support setup of boat stability</td>
</tr>
<tr>
<td>Impeller</td>
<td>Boat</td>
<td>Measure speed relative to the water [74]</td>
</tr>
<tr>
<td>GPS</td>
<td>Boat</td>
<td>Measure distance and speed relative to the shore [74]</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Boat</td>
<td>Measure stroke rate [74]</td>
</tr>
<tr>
<td>Gyroscope</td>
<td>Oars</td>
<td>Measure influence on boat stability [83]</td>
</tr>
<tr>
<td></td>
<td>Boat</td>
<td>Measure boat stability [44, 105]</td>
</tr>
<tr>
<td>Potentiometer</td>
<td>Boat</td>
<td>Measures horizontal oar angle [37]</td>
</tr>
<tr>
<td>Force sensor</td>
<td>Oarlocks</td>
<td>Measure force applied to oars [92]</td>
</tr>
<tr>
<td></td>
<td>Foot stretcher</td>
<td>Measure force on foot stretcher</td>
</tr>
<tr>
<td>Strain gauge</td>
<td>Oars</td>
<td>Measure bending force on oars</td>
</tr>
</tbody>
</table>

Table 11: Overview of sensing approaches in rowing boats. © 2011 IEEE
Several approaches [63] have been suggested to perform biomechanical analysis of rowing technique. Various research has considered indoor rowing, i.e. ergometers [19, 58, 17] or rowing simulators [103], however, in this paper we will focus only on solutions for actual rowing boats in the water. We suggest to use unobtrusive sensor networks as described in the following section.

7.2.4 IMU-based Support to Optimize Rowing Technique

To address the need to provide the coach with additional information for optimizing a rower’s technique, we have investigated the application of sensor networks in rowing boats. These sensors enable quantitative measurements of certain aspects of rowing technique which are related to the overall rowing performance desired. Our approach is to continuously monitor oar and boat orientation for each rowing stroke and subsequently quantify and visualize a subset of established rowing technique indicators. The lower part of Figure 51 illustrates the proposed extension of the standard approach. The length of each rowing stroke is just one example of a movement, which a coach cannot observe accurately just with their eyes. Sensor networks can support the coach in this aspect.

We have found that IMUs are well suited to continuously and unobtrusively monitor important indicators relating to rowing technique such as the stroke length and the stroke rate. Figure 54 depicts typical signals for the three orientation angles measured with an IMU on the oar. The definition of the orientation angles is given in Figure 53. As shown in Figure 54 we calculate the catch and finish phase from the horizontal oar angle. Based on this we deduce the stroke rate, the stroke length, the ratio of recovery/drive, and the variance of these parameters. Based on the oar rotation angle we determine for each point in time if the blade is feathered or squared. The vertical oar angle indicates the depth of the blade relative to the boat. In the following we will focus on IMUs as they represent promising sensors for our task.
Figure 53: Definitions of the three oar orientation angles: rotation (a), horizontal (b), and vertical (c). © 2011 IEEE

Figure 54: Typical signals for the three orientation angles measured on an oar with our system. Shown are 3 strokes at stroke rate 20. © 2011 IEEE
7.3 Implementation of an IMU-based Sensor Network for Rowing Boats

7.3.1 Pre-study

The design of a sensor network for rowing boats in naturalistic, harsh environments requires that the device is robust. Moreover, when deploying the system in real-world settings it is necessary that the rower is not hindered by a bulky measurement setup. Therefore, an unobtrusive sensing approach is essential to obtain realistic data.

In a pre-study [45] we optimized the type of sensors, the sensor positions, the number of sensors and the sampling rate of the sensors to achieve a reasonable trade-off between required accuracy and used resources. We visualized data from 12 different sensor locations of 10 recording sessions with 5 participants. We found that two IMUs, positioned on an oar and on the boat, are sufficient to address our research questions. The sensor on the oar provides the orientation data explained above. The sensor on the boat provides data of the boat’s acceleration and allows us to calculate a differential signal to assure that the oar orientation data is independent of the absolute boat movement, e.g. that induced by wavy water or a change of the heading. Movements in rowing happen quickly, especially in the catch phase. For our analysis the system’s maximum sampling rate of 60 Hz was sufficient.

7.3.2 Sensor Network

In the final setup we use three off-the-shelf IMUs from Xsens Technologies. The Xsens MT9 motion tracking system provides accurate orientation data (±0.05°) with a sufficient dynamic range of the angular velocity (±900°/s). As most of the athletes follow a strict training plan we have been granted only a limited amount of time to perform successful recordings. So, we extended the optimal setup found in the pre-study with an additional sensor on the second oar for redundancy. Figure 55 shows the sensors at-
tached to the two oars and the boat. Each IMU measures magnet field, acceleration and angle velocity in all three axis to calculate orientation angles. All IMUs are connected to an Xbus Master device to assure synchronized data. In this study we used a wired system, which stores the recorded data locally. Data recording and synchronisation was handled using the Context Recognition Network (CRN) Toolbox [23]. Later, it was transferred to the coach’s computer to perform the analysis. The runtime of one set of batteries was about two hours. We experienced no problems concerning data loss. The system can be installed in any type of rowing boat, and is useful for both sculling and sweep rowing. It provides useful data for any size of rowing boat from singles to eights.

![Inertial Measurement Units (IMUs)](image)

Figure 55: Implementation of the sensor network: Three IMUs on the oars and the boat, indicated by red arrows. © 2011 IEEE

### 7.3.3 Algorithms

Based on the raw data from the IMUs we have quantified various rowing technique indicators:

**Stroke Rate:** The stroke rate is a standard rowing parameter defined as the number of strokes per minute (spm). We compute the stroke rate by counting the frequency of the maxima of the horizontal oar angle. We apply a
peak detection algorithm and calculate the stroke time as the distance between the last two maxima. The reciprocal value is the stroke rate.

**Stroke Length:** We calculate the stroke length as the angle the oar sweeps in the horizontal plane from the catch position to the finish position. We recognize the catch (finish) position by detecting the minimum (maximum) of the horizontal oar angle. We calculate the stroke length from the peak-to-peak amplitude of the horizontal oar angle signal. The actual path length (in meters) that the blade travels in the water depends on the boat settings and is proportional to the angle we calculate.

**Ratio Recovery/Drive:** The ratio of drive phase to recovery phase is commonly used to characterize the rhythm in rowing. Beginners are particularly advised to keep a ratio of about 2:1 to assure calm sliding to the catch position and to accelerate the blade through the water to the finish. We detect drive and recovery phase based on the maxima and minima of the horizontal oar angle as indicated in Figure 54.

**Ratio Feathered/Squared:** We use a threshold at 45° on the rotation signal to detect the state of the blade for each point in time as indicated in Figure 54. The point in time to square up the blade is used to characterize the rhythm in rowing. Beginners are particularly advised to square up early to be prepared in time for a good catch.

The algorithms are computationally lightweight to eventually be implemented on wireless sensor nodes with restricted processing resources. The transmission of calculated features rather than raw data reduces the bandwidth requirements.

### 7.4 Application on the Water

We deployed the system in both training and racing conditions. Here we recorded data on the water in skiff racing boats (one person in the boat) from different brands (Stämpfli, Filippi, Weidnauer, Empacher). Since rowing technique is individually different we recorded data for 18 participants (age 15-53, weight 59-91 kg, height 174-190 cm). The subjects’ rowing experiences ranged from ambitious amateurs to national team rowers
(Germany and Switzerland) including current world champions and a current Olympic medallist. For sake of completeness we provide the basic parameters for all 18 participants measured in Table 12. Using the example of two rowers, we demonstrate in detail how our system could integrate into the iterative rowing technique optimization process illustrated in Figure 51. Due to space restrictions in this paper we have focused on two rowers, R1 (a current Olympic silver medallist) and R2 (a current U23 world champion). Table 12 also includes results for amateur rowers whose rowing technique can be analysed in the same way. The rowing technique indicators show differences between the amateurs and the more experienced rowers, especially in the training sessions. For both the racing and the training sessions the stroke length of the amateurs is on average shorter (race: 102°<106°; training: 103°<109°) and shows a higher standard deviation (race: 2.38°>2.16°; training: 2.78°>2.04°).
<table>
<thead>
<tr>
<th>Rower</th>
<th>stroke length</th>
<th>stroke rate</th>
<th>recovery/drive</th>
<th>feathered/squared</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Racing World-class Rowers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R1</td>
<td>106.56 (1.54)</td>
<td>28.64 (1.11)</td>
<td>0.90 (0.03)</td>
<td>0.43 (0.01)</td>
</tr>
<tr>
<td>R2</td>
<td>101.36 (2.29)</td>
<td>31.56 (0.72)</td>
<td>0.90 (0.03)</td>
<td>0.40 (0.01)</td>
</tr>
<tr>
<td>R3</td>
<td>107.36 (2.99)</td>
<td>32.11 (1.48)</td>
<td>1.01 (0.05)</td>
<td>0.44 (0.01)</td>
</tr>
<tr>
<td>R4</td>
<td>104.91 (2.31)</td>
<td>30.51 (0.62)</td>
<td>1.08 (0.05)</td>
<td>0.42 (0.01)</td>
</tr>
<tr>
<td>R5</td>
<td>104.49 (3.14)</td>
<td>32.26 (1.22)</td>
<td>0.96 (0.03)</td>
<td>0.42 (0.01)</td>
</tr>
<tr>
<td>R6</td>
<td>107.10 (1.48)</td>
<td>31.90 (1.48)</td>
<td>0.94 (0.03)</td>
<td>0.41 (0.01)</td>
</tr>
<tr>
<td>R7</td>
<td>112.51 (1.65)</td>
<td>33.15 (2.40)</td>
<td>0.96 (0.06)</td>
<td>0.41 (0.02)</td>
</tr>
<tr>
<td>R8</td>
<td>107.45 (2.16)</td>
<td>29.11 (0.80)</td>
<td>1.04 (0.04)</td>
<td>0.42 (0.02)</td>
</tr>
<tr>
<td>R9</td>
<td>102.09 (1.89)</td>
<td>35.93 (1.51)</td>
<td>0.84 (0.03)</td>
<td>0.33 (0.02)</td>
</tr>
<tr>
<td><strong>Racing Ambitious Amateurs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R10</td>
<td>101.23 (3.65)</td>
<td>24.93 (1.08)</td>
<td>1.28 (0.08)</td>
<td>0.44 (0.04)</td>
</tr>
<tr>
<td>R11</td>
<td>97.13 (2.51)</td>
<td>26.01 (0.77)</td>
<td>1.15 (0.07)</td>
<td>0.48 (0.02)</td>
</tr>
<tr>
<td>R12</td>
<td>106.27 (1.41)</td>
<td>31.76 (1.04)</td>
<td>1.00 (0.03)</td>
<td>0.38 (0.01)</td>
</tr>
<tr>
<td>R13</td>
<td>103.98 (2.10)</td>
<td>28.56 (0.49)</td>
<td>1.01 (0.04)</td>
<td>0.44 (0.01)</td>
</tr>
<tr>
<td>R14</td>
<td>98.43 (2.10)</td>
<td>26.57 (0.92)</td>
<td>1.05 (0.06)</td>
<td>0.44 (0.02)</td>
</tr>
<tr>
<td>R15</td>
<td>104.12 (1.67)</td>
<td>25.21 (0.79)</td>
<td>1.07 (0.05)</td>
<td>0.41 (0.02)</td>
</tr>
<tr>
<td>R16</td>
<td>105.67 (2.48)</td>
<td>30.68 (0.98)</td>
<td>0.86 (0.02)</td>
<td>0.38 (0.01)</td>
</tr>
<tr>
<td>R17</td>
<td>97.99 (3.95)</td>
<td>26.75 (1.63)</td>
<td>1.07 (0.12)</td>
<td>0.49 (0.03)</td>
</tr>
<tr>
<td>R18</td>
<td>107.31 (1.58)</td>
<td>25.65 (0.91)</td>
<td>1.15 (0.07)</td>
<td>0.45 (0.02)</td>
</tr>
<tr>
<td><strong>Training World-class Rowers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R1</td>
<td>114.82 (0.87)</td>
<td>19.75 (0.46)</td>
<td>1.59 (0.00)</td>
<td>0.52 (0.00)</td>
</tr>
<tr>
<td>R2</td>
<td>107.50 (1.75)</td>
<td>18.47 (0.42)</td>
<td>1.66 (0.01)</td>
<td>0.55 (0.00)</td>
</tr>
<tr>
<td>R3</td>
<td>108.16 (2.83)</td>
<td>18.37 (0.62)</td>
<td>1.86 (0.01)</td>
<td>0.58 (0.00)</td>
</tr>
<tr>
<td>R4</td>
<td>108.34 (3.19)</td>
<td>17.36 (0.39)</td>
<td>1.87 (0.01)</td>
<td>0.57 (0.00)</td>
</tr>
<tr>
<td>R5</td>
<td>109.24 (2.28)</td>
<td>20.78 (0.68)</td>
<td>1.54 (0.01)</td>
<td>0.53 (0.00)</td>
</tr>
<tr>
<td>R6</td>
<td>107.26 (1.96)</td>
<td>19.36 (0.42)</td>
<td>1.80 (0.00)</td>
<td>0.55 (0.00)</td>
</tr>
<tr>
<td>R7</td>
<td>113.41 (1.35)</td>
<td>20.41 (0.39)</td>
<td>1.59 (0.00)</td>
<td>0.55 (0.00)</td>
</tr>
<tr>
<td>R8</td>
<td>107.58 (2.21)</td>
<td>19.33 (0.42)</td>
<td>1.63 (0.00)</td>
<td>0.52 (0.00)</td>
</tr>
<tr>
<td>R9</td>
<td>106.35 (1.93)</td>
<td>19.84 (0.39)</td>
<td>1.58 (0.00)</td>
<td>0.46 (0.00)</td>
</tr>
<tr>
<td><strong>Training Ambitious Amateurs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R10</td>
<td>105.01 (4.25)</td>
<td>19.30 (0.45)</td>
<td>1.58 (0.01)</td>
<td>0.47 (0.00)</td>
</tr>
<tr>
<td>R11</td>
<td>99.58 (1.36)</td>
<td>17.18 (0.48)</td>
<td>1.71 (0.03)</td>
<td>0.59 (0.00)</td>
</tr>
<tr>
<td>R12</td>
<td>104.95 (2.73)</td>
<td>17.59 (0.60)</td>
<td>1.63 (0.01)</td>
<td>0.55 (0.00)</td>
</tr>
<tr>
<td>R13</td>
<td>106.06 (2.21)</td>
<td>23.10 (0.57)</td>
<td>1.23 (0.00)</td>
<td>0.47 (0.00)</td>
</tr>
<tr>
<td>R14</td>
<td>98.59 (2.21)</td>
<td>24.10 (0.83)</td>
<td>1.15 (0.01)</td>
<td>0.48 (0.00)</td>
</tr>
<tr>
<td>R15</td>
<td>98.38 (2.46)</td>
<td>18.09 (0.71)</td>
<td>1.30 (0.01)</td>
<td>0.52 (0.00)</td>
</tr>
<tr>
<td>R16</td>
<td>106.29 (1.36)</td>
<td>20.54 (0.40)</td>
<td>1.33 (0.00)</td>
<td>0.45 (0.00)</td>
</tr>
<tr>
<td>R17</td>
<td>108.85 (5.53)</td>
<td>19.52 (1.02)</td>
<td>1.57 (0.03)</td>
<td>0.59 (0.00)</td>
</tr>
<tr>
<td>R18</td>
<td>102.84 (2.93)</td>
<td>15.80 (0.54)</td>
<td>1.79 (0.01)</td>
<td>0.61 (0.00)</td>
</tr>
</tbody>
</table>

Table 12: Basic rowing technique indicators for all 18 participants for training and the steady-state rowing part during the race. In brackets the standard deviation is given. © 2011 IEEE
7.4.1 Procedure

For each participant we recorded both a training and a racing session. The training session comprised 1000 m of rowing with a constant stroke rate between 18 and 21 spm, focusing on good technique. The racing session comprised 1000 m of rowing in racing conditions against another boat aiming to achieve the minimum possible time and with an unlimited stroke rate. Before each session, the rowers were instructed to perform calibration movements used to adapt the system to the boat and mounting settings. Namely, each rower moves to the catch, middle and finish positions and holds each position for seven seconds. Afterwards, the participants were asked whether they felt impaired by the system or could row naturally. The test time for both sessions in total was about 30 minutes per participant. Installing and removing the sensors took an additional 15 minutes per participant. In total we recorded over 10 hours of data.

7.4.2 Results and Discussion

All participating rowers stated that they were not impaired by the system and could row naturally. So, we consider the system sufficiently unobtrusive to record realistic data.

Figure 56 depicts for rower R1 the result of a continuous monitoring of the stroke rate, stroke length, ratio recovery/drive and ratio feathered/squared for both racing and training. Considering the visualization of the racing session, the rower’s race strategy can be identified: The race begins with a high stroke rate (>40 spm), then the stroke rate drops and remains constant in the steady-state rowing phase (about 30 spm). Finally, the stroke rate increases again for the final sprint. During the high stroke rates the minimum time for the drive phase is limited by the rower’s strength and water resistance. To achieve an increased stroke rate the rower usually shortens the recovery time. So, the ratio recovery/drive is lower than for the training session. The relatively reduced time for the recovery phase also causes the ratio feathered/squared to drop. In racing the rower tries to focus on good technique and attempts to execute each stroke in the same way as he did at a reduced stroke rate during training.
Stroke Rate and Stroke Length: Stroke length and stroke rate are two of the main important rowing technique indicators. Figure 57 depicts the stroke length over the stroke rate for two rowers, R1 and R2, for both training and racing. As in Figure 56 the stroke length decreases as the stroke rate increases for both R1 and R2. During races a broader range of stroke rates occurs. The race starts and finishes with final sprints and therefore higher stroke rates are achieved during these phases of the race (see Figure 56). The race phases are represented in clusters and are marked with col-
ours exemplarily for R1. Here we observe a linear correlation between stroke rate and stroke length. The corresponding slope is lower for R1 than for R2. This means that R1 can keep a higher stroke length, even at an increased stroke rate. R1 shows a low variance in the stroke length and stroke rate and a high absolute stroke length and maximum stroke rate. In the steady-state rowing phase R1 and R2 follow two different rowing styles: R1 performs longer strokes at a lower stroke rate compared to R2. R2 compensates the shorter stroke length with a higher stroke rate.

![Figure 57: Visualization of data of stroke length and stroke rate from two world-class rowers (R1 and R2) for training and racing sessions. © 2011 IEEE](image)

**Detailed Analysis of Stroke Length**: Coaches can use our system to analyse variations in the stroke length in more detail. The variance of the absolute stroke length might result from a variance in the catch position, the finish position or both. Figure 58 depicts the horizontal oar angle over time for rower R3; this is similar to that in Figure 54. In this example the variance in the finish position is the main contributor to the variability of the overall stroke length. Based on the output of the system the coach is able to advise the rower to perform dedicated exercises to strengthen the muscles which support a stable finish position. This example demonstrates the benefit of our system for the training process.
Figure 58: Stroke length is shown in detail: In this example the variability of the stroke length results mainly from a variance in the finish position. © 2011 IEEE

**Rhythm:** Figure 59 depicts the oar rotation angle over the horizontal oar angle. This visualization supports the coach in analysing the rhythm and helps to identify rowers who square up early or late. How fast the squaring of the blade takes place is indicated by the distance between the dotted red vertical lines. Also, the stability of the blade in the water during the drive phase and in the air during the recovery phase is characterized. In this example we observe an over-rotation for R2 after extracting the blade from the water.

![Graph showing oar rotation angle over horizontal oar angle for rowers R1 and R2 for both training and racing sessions.](image)

Figure 59: Oar rotation angle over the horizontal oar angle for rowers R1 and R2 for both training and racing sessions. For visualization the curve for R2 is shifted 10° to the lower left corner. © 2011 IEEE

**Boat Acceleration:** Figure 60 depicts the boat acceleration in driving direction over the horizontal oar angle. This allows the coach to analyse the
impact of changes in different phases of the rowing cycle on the boat acceleration. In this example, the coach could observe an irregularity on the mid-stroke position of subject R2 during racing conditions. Usually, a rower reaches the maximum acceleration during the middle of the stroke, in this case there is a local minimum.

![Figure 60: Boat acceleration in driving direction over horizontal oar angle to illustrate how the movement of the oar through the water accelerates the boat. © 2011 IEEE](image)

### 7.5 Conclusion and Outlook

By collaborating with national rowing coaches, we have identified important indicators relating to rowing technique. We have found that IMUs are suitable for measuring a subset of these rowing technique indicators. In a feasibility study we have investigated the optimal sensor setup. Our final sensor setup consists of two IMUs on the oars and one on the boat. For evaluation on the water we have selected 18 participants whose experience level ranged from ambitious amateurs to world-class rowers. For each we have recorded a training and a racing session each of which consisted of 1000m rowing. We have shown that we are able to measure rowing technique indicators such as stroke length and stroke rate for both amateurs and world-class rowers. Using the data derived from two world-class rowers we have demonstrated how our system supports the iterative process of optimizing rowing techniques. In our approach the coach as an expert is in the loop, who integrates the overall context such as the wind, water and
boat conditions, body height, or the individual style of the rower concerned to come up with holistic conclusions.

Our next steps are to use wireless IMUs for easier application and to investigate the influence of potential packet loss and sensor sampling rate. We also plan to monitor the rower’s body postures to capture additional rowing technique indicators, to provide condensed information using real-time feedback and to evaluate the benefit of the system in a long-term study.

Our vision is a rowing boat that is equipped with an unobtrusive Rowing Boat Area Network (RBAN) that continuously monitors the rower’s technique for both offline analysis and real-time feedback. We see potential in a modular RBAN that seamlessly and comfortably integrates into the rower’s equipment. Depending on the requirements a set of dedicated sensors (e.g. on-body or physiological sensors) could monitor rowing performance indicators like physical strength, mental strength, boat stability and synchronicity in crew boats. We believe that taking advantage of the progress in intelligent sensors and communication technology will help to push the boundaries of the sport.

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Chapter 8  SonicSeat: Seat Position Tracker based on Ultrasonic Sound Measurements

Franz Gravenhorst, Christoph Thiem, Bernd Tessendorf, Rolf Adelsberger, Bert Arnrich, Conny Draper, Richard Smith, Gerhard Tröster

Original publication title: SonicSeat: Design and Evaluation of a Seat Position Tracker based on Ultrasonic Sound Measurements for Rowing Technique Analysis

Journal of Ambient Intelligence and Humanized Computing

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Abstract

A significant number of rowers do not receive technical coaching. However, proper technique is a key component both for achieving competitive success and in preventing injuries or long-term induced postural deformity. In cooperation with national rowing coaches we developed a sensor system to continuously monitor rowers’ seat positions, enabling us to evaluate their rowing technique. We use offline data analysis, which complements existing state-of-the-art methods based on video footage. Both quantitative analyses for coaches as well as qualitative and visual feedback for athletes is provided. We evaluated the accuracy of the SonicSeat system in a lab environment and obtained mean relative errors between 0.74% and 2.36% for all but one of our performance metrics. We tested our system on the water and present exemplary data and analyses.

8.1 Introduction

Rowing is one of the oldest Olympic disciplines and is very popular for both spectators and athletes. The rowing population is growing by 5% annually in the United States [12]. Junior, high school, collegiate and elite athletes are usually members of a well-structured and supervised rowing program, while older adult rowers are usually in less organized squads and often receive only minimal supervision from coaches. The adult rowers demographic is significant, almost doubling between 2004 and 2008 [12]. However, the lack of coaching many older rowers receive means they are less likely to master rowing’s complex motion sequence, reducing their chance of winning races and increasing the likelihood of injury [15]. There is a broad knowledge about the ideal rowing technique [15, 37]. To teach technical skills, coaches mostly rely on their eyes and simple technical tools like video cameras [45]. However, coaches are not available all of the time and there is a need to support rowers with automatic tools to enable self-assessment, especially when no coach is available [36].
8.1.1 Rowing Technique

Rowing is a sequence of strokes with the goal of moving the boat forward as fast as possible. One stroke of the basic rowing technique is illustrated in Figure 61. From the finish position (1) the rower stretches his arms and leans his upper body forward. Subsequently, the rower moves his sliding seat to the stern by bending his legs. This recovery phase (2) ends with the catch (3) where the blades are placed in the water. During the drive phase (4) the rower moves the boat forward by pulling the oars. This is achieved by extending and pushing the legs (4) and then pulling with the upper body and arms (5). In the finish position (6) the rower levers the oar blades out of the water and feathers them parallel to the water's surface until the next catch position is reached.

![Figure 61: One cycle of rowing [10]](image)

The sliding seat allows the rowers to use their legs to achieve a longer and more powerful stroke compared to a fixed seat. The legs are the most powerful limbs involved in rowing, contributing 70% of the total expended energy. At the same time, the sliding seat movement is also one of the most sensitive parts of the stroke. The sliding of the seat goes in line with the movement of the rower’s body. The weight of the rower is typically at least five times higher than the boat’s weight. Thus, the sliding seat move-
ment is directly linked to the movement of the center of gravity. Proper technique for moving the sliding seat is essential to avoid unintended vertical or rotational movements of the boat. This stabilizes the boat, minimizes the loss of speed and minimizes the risk of injury. Thus, the right coordination of the legs is, for both beginners and advanced rowers, an essential and challenging part of rowing technique.

8.1.2 Previous Work

In previous work we proposed a boat area network, which consists of multiple inertial measurement units, which are attached to the boat and the oar [44, 45, 102]. Based on the measured data, the orientations and movements of the boat and the oar were analysed. With this system, coaches and rowers are able to benchmark their oar movement patterns to the ones of other rowers in an objective, quantitative way. However, the movement of the oar is the result of the coupled and coordinated actions of multiple sub-movements of many limbs. Knowing the resulting oar movement, it is still hard to derive causes for deviations and propose appropriate suggestions on how to improve the technique. The two sub-movements known to influence the oar movement the most are the swing of the rower’s upper body and the sliding of the seat [37].

In this work we extend our existing boat area network with an additional sensor node to track the position of the sliding seat. We explore the technical feasibility and potential of such a new subsystem.

8.1.3 Related Work

The most common system to monitor the sliding seat movement is the StrokeCoach device by NielsenKellermann [74]. It is a commercial device to count the seat movements with a magnet and a reed switch. The goal of the system is to calculate and display the current stroke rate. There is no possibility to continuously monitor the seat position.

Kleshnev [63] and Smith [96] present a method to measure the seat position based on a cord, which is connected to a potentiometer. The cord is
attached to the sliding seat. Measurements can be made in an easy and stable way. However, the system interferes directly with the rower as the attached cord constantly pulls the seat backward.

Davoodi presented a system to track the seat position by optical methods [33]. This system works well for indoor rowing. However, this approach is not yet tested for on-water environments.

8.1.4 Contributions

This work aims to advance the state of the art in the following aspects:

- We describe the design and implementation of a contactless measurement system for monitoring the sliding seat’s movements in on-water environments.
- We evaluate the accuracy of the system against an optical motion tracking system in a dry lab environment.
- We demonstrate the technical feasibility in a proof-of-concept study on the water.
- We introduce quantitative performance metrics to rate rowing technique based on sliding seat movements.
- We provide a fully automated rowing data analysis tool to calculate and visualize these metrics.
- We extend the most common current approach of analysing rowing technique based on inspection of video footage, by adding two new functionalities: the automatic segmentation of strokes and the inclusion of subtitles.
8.2 Seat Position Tracking System

8.2.1 Requirements

In discussions with professional rowing coaches and athletes of different skill levels we identified the following requirements for an ideal seat position tracking system:

- **Continuous measurements.** The system should be able to record continuous data of a whole training session, which usually lasts between one and two hours. The system must be easy to use, e.g., not require the user to change batteries or storage volumes during the session.

- **Unobtrusiveness.** The rower should be distracted or influenced by the system as little as possible. This implies a small form factor and weight of the system and contactless measurement methods.

- **Accuracy.** The system’s accuracy should be at least comparable to the perception skills of an experienced coach.

- **Rules.** To allow the usage of the system in competitions, the appropriate racing rules have to be respected. All international rowing competitions and most of the national rowing federations implement the FISA\(^2\) rules of racing [35], which prohibit any devices that enable communication outside of the boat. Therefore, the system either has to feature live feedback capabilities for the rower or record the data for later offline analysis.

\(^2\) The Fédération Internationale des Sociétés d’Aviron (FISA) is the international rowing federation.
8.2.2 Seat Tracking based on Ultrasonic Sound

We propose a contactless seat tracking system based on ultrasonic sound distance measurement. In a pre-study we optimized the system configuration and mounting to the boat. In the following we describe the final setup.
We opted for the Devantech SRF08 Ultrasonic Range Finder. It represents a low-cost (<50) module comprised of an ultrasonic sound transceiver. Technical specifications are listed in Table 13.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Devantech Ltd.</td>
</tr>
<tr>
<td>Model</td>
<td>SRF08</td>
</tr>
<tr>
<td>Size</td>
<td>43x20x17 mm$^3$</td>
</tr>
<tr>
<td>Size incl. housing</td>
<td>55x34x30 mm$^3$</td>
</tr>
<tr>
<td>Weight incl. housing</td>
<td>19 g</td>
</tr>
<tr>
<td>Current Consumption (ranging)</td>
<td>12 mA</td>
</tr>
<tr>
<td>Current Consumption (standby)</td>
<td>3 mA</td>
</tr>
<tr>
<td>Voltage</td>
<td>5 V</td>
</tr>
<tr>
<td>Measuring steps</td>
<td>4 µs (equals ~ 0.9 mm)</td>
</tr>
<tr>
<td>Connection</td>
<td>I²C Bus</td>
</tr>
<tr>
<td>Accuracy</td>
<td>4 cm</td>
</tr>
</tbody>
</table>

Table 13: Specifications Ultrasonic Range Finder [13]

The module is aligned to the boat with the ultrasonic beam pointing towards the sliding seat as depicted in Figure 62. During the pre-study we discovered that locating the module behind the seat was favorable in comparison to positioning it in front of it: This way, the module does not interfere with the rower’s legs and the system disappears from the rower’s sight. The module sends out sound bursts at a frequency of 40 kHz and measures the time interval until the echo is received. With the measured sound travel time $t_i$, the sound velocity in air $c_{\text{Air}}$ and the distance $s$ between transmitter and receiver, the position $h$ of the sliding seat can be obtained according to equation (16)

$$h(t_i) = \sqrt{\left(\frac{c_{\text{Air}(T)}t_i}{2}\right)^2 - \left(\frac{s}{2}\right)^2}$$ (17)
The sound velocity in air $c_{\text{Air}}$ depends on the current air temperature $T$:

$$c_{\text{Air}}(T) = 331.5 \frac{m}{s} \sqrt{1 + \frac{T/\degree C}{273.15}}$$  \hspace{1cm} (18)

In our pre-study we measured a maximum temperature variation during one training session of 4 K (15$\degree$C to 19$\degree$C). For the sake of simplicity, we calculate the average temperature and assume this to be the constant temperature during one measurement session. This simplification introduces a maximum error of less than 1%.

The sensor module is connected through its I²C bus interface to a data logger to save the data to a SD card. The maximum sampling frequency is limited by the maximum travel time $t_{\text{max}}$, which the sound needs for the maximum expected seat distance $h_{\text{max}}$:

$$f_{\text{max}} = \frac{1}{t_{\text{max}}} = \frac{c_{\text{Air}}(T)}{2} \left( h_{\text{max}}^2 + \left( \frac{s}{2} \right)^2 \right)^{-0.5}$$  \hspace{1cm} (19)

The upper limit for our setup calculates to $f_{\text{max}} \approx 160$ Hz. We chose a sampling frequency of $f_s = 100$ Hz, which we found to be sufficient for our application.

### 8.3 Training Analysis

#### 8.3.1 Performance Metrics

As outlined in section 8.1.1 the proper movement of the sliding seat is a key component for good rowing technique. Coaches and rowing literature offer a broad variety of advice on what an ideal seat movement should be. In this work we focus on the most important features as described by leading rowing associations [15, 35, 37]. Based on the qualitative descriptions in literature and in collaboration with national rowing coaches of Germany
and Switzerland we propose measures which represent the rower’s performance quantitatively.

The described measures are visualized in Figure 63 and are characterized in the following section.

Figure 63: Sliding seat movement during one rowing cycle. Extracted performance metrics are the ratio between recovery (1) and drive (3) phase duration, the catch delay $\Delta t_{\text{delay,n}}$ (2), the total seat displacement $\Delta h_n$ (5), and the ratio between the time needed for the full slide (1) and the last third of the slide (6). Label (4) depicts the tolerance interval $\Delta h_{\text{tol}}$ during which deviations from the catch or finish position are still considered as pause. (Pictures have been taken from [10].)
8.3.1.1 Stroke Rate

The seat movement is segmented into $N$ separate strokes by detecting the local minimums that represent the finish positions.

$$h(T_n) = h(t_{\text{finish},n}) = h_{\text{min},n}, \ n = 1..N \quad (20)$$

The stroke rate $f_{\text{rate},n}$ is the reciprocal time interval between two strokes. It is measured in strokes per minute:

$$f_{\text{rate},n} = (T_{n+1} - T_n)^{-1}, \ n = 1..(N - 1) \quad (21)$$

8.3.1.2 Catch Delay

In the catch position the center of gravity is located at the stern of the boat. The longer the pause at this position, the more the boat’s stern rotates into the water and decelerates the boat. Therefore, the blade should go into the water and start the next stroke as soon as the most forward position, the catch, is reached. The catch position is represented by the local maximum of the $h(t_i)$ curve:

$$h(t_{\text{catch},n}) = h_{\text{max},n} = \max_{t_i \in (T_n; T_{n+1})} (h(t_i)) \quad (22)$$

We define the catch delay $\Delta t_{\text{delay},n}$ as the length of the time interval during which the seat position resides within the range of $\pm \Delta h_{\text{tot}} = 4 \ cm$. The range is chosen according to the expected measurement accuracy of the ultrasonic measurement module.

Finally, we compensate for variations of the current stroke rate $f_{\text{rate},n}$ and normalize the catch delay to a stroke rate of $f_{\text{norm}} = 20/min$: 
\[ \Delta t_{\text{delay, norm}, n} = \Delta t_{\text{delay, } n} \cdot \frac{f_{\text{norm}}}{f_{\text{rate, } n}} \]  

(23)

### 8.3.1.3 Sliding Seat Displacement

The rower should stick to a long stroke length, even with high stroke rates, for example during racing conditions [37]. Besides the arm and upper body movement, the sliding seat displacement \( \Delta h_n \) is the main contributor to achieve a long stroke length:

\[ \Delta h_n = h_{\text{max, } n} - h_{\text{min, } n} \]  

(24)

### 8.3.1.4 Maximum Sliding Velocity

The sliding seat should move in a uniform smooth motion. Sharp acceleration and velocity peaks cause unintended boat movements and vibrations and should be avoided.

We derive the seat velocity \( v(t_i) \) as the difference between two successive discrete seat positions:

\[ v(t_i) = s \cdot (h(t_{i+1}) - h(t_i)) \]  

(25)

The maximum seat velocity is calculated as the highest positive peak within the time interval of one stroke (see Figure 64):

\[ v_{\text{max, } n} = \max_{t_i \in (T_n, T_{n+1})} (v(t_i)) \]  

(26)

Again, this measure is normalized to stroke rate \( f_{\text{norm}} \):

\[ v_{\text{max, norm, } n} = v_{\text{max, } n} \cdot \frac{f_{\text{norm}}}{f_{\text{rate, } n}} \]  

(27)
Figure 64: Sliding seat movement (black line) and seat velocity (blue line) during one rowing cycle. Label (7) depicts the maximum sliding velocity $v_{max,n}$.

### 8.3.1.5 Ratio Drive/Recovery

There is controversy among coaches concerning the ideal value for the ratio between drive and recovery phase durations. The ideal value is individual for every crew and depends on boat class, crew weight, gender and experience. Beginners are told to aim for a drive/recovery ratio of 1:2 \[102\], which means the recovery time is double the drive time.

To calculate the ratio, we define the duration of the drive phase and recovery phase respectively as the interval where the major seat movements happen: The recovery phase begins as soon as the seat position differs more than $\Delta h_{tol}$ from the finish position $h(t_{finish,n})$ (see equation 4). It ends as soon as the seat is closer than $\Delta h_{tol}$ to the catch position $h(t_{catch,n})$ (see equation 6). Similarly, the drive phase begins as soon as
the seat deviates by more than $\Delta h_{tol}$ from the catch position $h(t_{catch,n})$ and ends in a distance of $\Delta h_{tol}$ before reaching the successive finish position $h(t_{finish,n+1})$.

8.3.1.6 Recovery Uniformity (Ratio of durations last third/full slide)

Besides avoiding high peak values for the sliding speed, coaches also consider the distribution of the sliding speed during the recovery phase to rate the uniformity of a stroke. A typical mistake for rowers is having an inconstant speed on the sliding seat; inexperienced rowers tend to accelerate the slide movement during the last part of the recovery.

The start and the end of the recovery phase is defined as described in the previous section. The total seat displacement $\Delta h_{recovery,n}$ which happens during the recovery phase is:

$$\Delta h_{recovery,n} = \Delta h_n - 2 \cdot \Delta h_{tol} \quad (28)$$

According to Figure 63 the following equations apply for the start time of the recovery phase $t_{recovery\_start,n}$, the time $t_{recovery\_share,n}$ when $\frac{2}{3}$ of the recovery distance is done, and the end time $t_{recovery\_end,n}$ of the recovery phase:

$$h(t_{recovery\_start,n}) = h(t_{finish,n}) + \Delta h_{tol} \quad (29)$$

$$h(t_{recovery\_share,n}) = h(t_{finish,n}) + \Delta h_{tol} + \frac{2}{3} \Delta h_{recovery,n} \quad (30)$$

$$h(t_{recovery\_end,n}) = h(t_{finish,n}) + \Delta h_{tol} + \Delta h_{recovery,n} \quad (31)$$

To calculate the uniformity measure $U_n$, the ratio between the time needed for the last third of the slide and the full slide is subtracted from $\frac{1}{3}$.
A negative value $U_n$ means the seat is decelerated in the last third of the slide. A positive value stands for an accelerated motion.

8.3.2 Data Analysis

8.3.2.1 Sliding Seat Data

After finishing the rowing workout, the data is transferred to a computer and then processed by our rowing data analysis tool. The tool is fully automated and does not require any user input. It performs the stroke segmentation and calculates the performance metrics for all strokes as described above. Additionally, for the normalized catch delay values a binary classification is performed to identify which strokes are significantly worse than average. The threshold value $\tau_{delay}$ for this classification is chosen as the sum of the median value and the standard deviation of the normalized catch delay:

$$\tau_{delay} = \text{median}(\Delta t_{delay,norm,n}) + \text{std}(\Delta t_{delay,norm,n})$$

Thus, the threshold value is different for each rower and each practice. Our method allows a quick identification of the outlying strokes, which potentially require most attention. A similar classification was performed for the maximum normalized sliding velocity values $v_{max,norm,n}$.

The resulting values can be inspected as a plain time series for custom computations, and they can also be visualized for every single stroke.
8.3.2.2 Video Footage

Our rowing data analysis tool offers the possibility to import video footage recorded during the practice. After synchronizing the video with the seat data, the video data is automatically segmented by strokes and annotated. This allows the rower or coach to replay specific stroke numbers or to watch and visually compare multiple strokes that have been identified by our algorithm as outliers in any respect. During the replay the analysis tool features continuously update performance evaluations or the current stroke number, displayed as subtitles within the video. An example is shown in Figure 65.

![Image](image.png)

Figure 65: For post-training analysis recorded video footage is automatically segmented into separate strokes and performance data or the stroke numbers is displayed as subtitles. [43]

8.4 Evaluation Experiment

8.4.1 Indoor Rowing Simulator Setup

To evaluate the accuracy of the quantitative measures, we opted for an indoor setup which allows the simultaneous recording of the seat position by our SonicSeat system as well as with a state-of-the-art optical motion tracking system. The indoor setup is depicted in Figure 66.
It includes a real rowing boat equipped with sensors and actuators and is surrounded by screens and loudspeakers. Further details of the virtual rowing simulator can be found in [103]. The motion tracking system (QTM, Qualisys AB, Gothenburg, Sweden) consisted of 5 cameras sampling at 200Hz.

The evaluation experiment included a variety of different rowing techniques, technical drills and common mistakes. In total, we recorded 51 strokes which included four different stroke lengths, delay at the finish position, delay at the catch position, slow sliding during recovery, fast sliding during recovery, and fast sliding during the drive phase.

![Rowing simulator](image)

**Figure 66:** Rowing simulator to record optical motion tracking data of the seat for evaluation.

### 8.4.2 Measurement Results

The calibration procedure for the motion tracking system was performed as advised by the manufacturer. The calibrated system reported an accuracy (residual) of \( e = 6.8 \cdot 10^{-4}m \). The optical marker which represented the seat position was tracked successfully throughout the whole experiment, no data loss occurred. The residual for the marker varied between \( 7.2 \cdot 10^{-4}m \) and \( 9.4 \cdot 10^{-4}m \) (mean±std: \( 8.3 \cdot 10^{-4}m \pm 2.5 \cdot 10^{-5}m \)).

The data recording of our SonicSeat system also experienced no data loss.
Both systems identified all 51 strokes. However, for the purpose of easier segmentation the motion was interrupted three times during the data recording. The affected three pairs of strokes were excluded from further calculations.

Based on the measured SonicSeat data, for every stroke $n$ all performance metrics $x_{\text{measured},n}$ were calculated. Similarly, the optical motion tracking data was used to calculate the reference performance metrics $x_{\text{reference},n}$. Finally, the relative error $x_{\text{error},n}$ was calculated:

$$x_{\text{error},n} = \frac{x_{\text{measured},n} - x_{\text{reference},n}}{x_{\text{reference},n}}$$ (34)

To compare both data sources in regards to the resulting automatic binary classification result, we calculated the share of strokes where both data sources lead to the same classification result.

The results of the relative errors as well as the matching classifications are summarized in Table 14.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Relative error Mean ± Std</th>
<th>Matching classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seat displacement</td>
<td>1.13% ± 0.75%</td>
<td>–</td>
</tr>
<tr>
<td>Catch delay, normalized</td>
<td>−1.42% ± 5.04%</td>
<td>100%</td>
</tr>
<tr>
<td>Max. sliding velocity, normalized</td>
<td>−30.12% ± 17.35%</td>
<td>93%</td>
</tr>
<tr>
<td>Ratio drive/recovery</td>
<td>−2.36% ± 2.32%</td>
<td>100%</td>
</tr>
<tr>
<td>Recovery uniformity</td>
<td>0.74% ± 3.51%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 14: Comparison of calculated metrics and classification resulting from SonicSeat measurements and from reference system (optical motion tracking).

Out of all proposed performance metrics, the normalized maximum sliding velocity was most prone for errors. One reason for this is the quantization error (see section 2.2), which is amplified by the discrete difference process. This error could be reduced by either changing the hardware or by
introducing a filter after the derivative process. Applying a sliding window averaging filter (length: 40 samples) to the velocity data would decrease the relative error to $-6.76\% \pm 12.29\%$ and increase the matching classification to 98%.

8.5 Application on the Water

In this section we present exemplary data from a rower who used the system during exercise on the water. To ensure diverse data, the rower was accompanied by a coach in a motorboat who prompted him to perform several technical drills aimed to provoke either good or bad technique. In total, the data set consists of 223 complete strokes. Additionally, the training session was recorded with a video camcorder. After the practice we used our rowing data analysis tool to examine the rower’s exercise. Exemplary results of two single strokes are shown and explained in Figure 67 and Figure 68. The first one shows a short stroke, which is considered average in respect to catch delay and seat velocity. The second stroke shows a longer catch delay and a significant peak in the sliding velocity. This bad technique is called “rushing the slide” and is a typical mistake made by rowers at beginner level [37].

We asked two experienced elite level (world cup) rowers to decide solely based on the recorded video footage which strokes they rate as “significantly worse than average” for the given dataset in respect to (A) catch delay and (B) unsmooth sliding motion. The remaining strokes were rated as “average”. In a first run, the experts drew their decisions individually. Then, they discussed the strokes where their individual rating differed until they agreed upon a common rating. We considered the expert’s rating as gold standard and compared it to the classifier’s result. The strokes which were recognized as worse by both the gold standard and the classifier were counted as true positives. The strokes which were rated as average by both the gold standard and the classifier were counted as true negatives.
Figure 67: Stroke number 210: The measured sliding seat displacement is 359 mm. The delay at the catch position is 27 ms. This value is marked with a green bubble, which highlights that this value is not considerably bad in comparison to the average stroke within the recorded session. [43]

Figure 68: Stroke number 60: In this example, the stroke length is 511 mm. The delay at the catch position is 41 ms, which is considered an extremely bad value and therefore is marked by a red bubble. Additionally, the peak in the velocity curve (bottom) is also significantly worse (red line) in comparison to the other strokes of the same session. [43]
In case the classifier disagreed with the gold standard the stroke was treated as false positive (experts rated *average* and classifier rated *worse*) or false negative (experts rated *worse* and classifier rated *average*). Based on these stroke counts, the specificity values and sensitivity values are calculated according to the following equations:

\[
Specificity = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}
\]  

\[
Sensitivity = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}
\]

(35)  

(36)

In respect to normalized catch delay (normalized maximum sliding velocity) the classifier achieved a specificity of 90% (98%) and a sensitivity of 100% (100%). An excerpt of the classification result in respect to catch delay for ~50 strokes is depicted in Figure 69.

![Figure 69: Comparison of automated classifier with expert’s rating. Red background color means that experts rated the catch delay of the stroke as “worse than average”. Red circles represent the analog rating as result of the automated classifier. [43]](image)
To induce different stroke lengths, the rower was instructed to perform a 400 m test race. The recorded data is shown in Figure 70. The data represents a typical race profile. This includes a start phase with short strokes at a high stroke rate, then a steady-state rowing phase with constant length and rate, and the final sprint with increasing stroke rates and decreasing seat movement amplitude.

Figure 70: Sliding seat displacements and stroke rates during a 400 m test race. [43]

8.6 Limitations

Although, we tried to meet most of the requirements mentioned in section 8.2.1, we are aware that this work is only one step towards the envisioned ideal system and it still has some limitations.

**Limited parameters.** Our approach only takes into account the sliding seat movement. Although, this aspect is of great interest for the rowing community, there are additional parameters of interest that are not yet covered by our system. We are in the process of extending the system accordingly.

**Single-User study.** The goal of this work is to motivate and describe the implementation of a new sensor modality for rowing technique monitoring
systems. To believe in a potential value of the system we rely on literature and feedback from experts. Although we conducted a user study, we cannot prove any statistical relevance due to too small user numbers. This work is a first step, which shows the technical feasibility and will be the foundation for a more significant user study to follow.

**Unobtrusiveness.** An ideal measurement system does not interfere with the measured object. Although we restricted the additional volume and weight, which was mounted to the boat to a minimum, the adjustments could still be influencing the rower knowingly or unknowingly.

### 8.7 Conclusion and Outlook

We presented a newly developed contactless seat position tracker for rowing boats based on ultrasonic sound measurements. We described the system design and presented exemplary data from a first on-water measurement.

In collaboration with rowing experts we identified performance metrics to rate rowing technique based on sliding seat movements and introduced quantitative representations. We presented a rowing data analysis tool, which calculates and visualizes these performance metrics. Additionally, it complements the state-of-the art method for analysing rowing technique by using video footage with two additional functionalities: the automatic segmentation of strokes and the inclusion of calculated performance metric values as subtitles.

We compared the SonicSeat data recording against a state-of-the-art optical motion tracker system and obtained mean relative errors between 0.74% and 2.36% for all but one performance metrics and always the same classification results. However, the normalized maximum sliding velocity suffered from quantization errors and yielded a mean relative error of -30.12% and only 93% of the strokes resulted in matching classification results.

In a next step we will integrate this new sensor modality into our existing boat area network [44, 45, 102]. For application in rowing training we will
include real-time feedback to the rower and coaches. The sensor network will be extended to rowing boats with more than one rower to analyse and improve crew synchronicity.

Acknowledgments

The authors gratefully thank Georg Rauter, Roland Sigrist and Prof. Roland Riener from Sensory Motor Systems Lab, ETH Zurich, Switzerland for their dedicated support in the recording of the optical motion tracking data. Further thanks go to all participants of the studies and pre-studies, and the collaborating coaches for their feedback. Last but not least, thanks to Rosa Brown (topproofreading.com) for proof-reading the manuscript.
Chapter 9  Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

Franz Gravenhorst, Amir Muaremi, Conny Draper, Margy Galloway, Gerhard Tröster

Original publication title: Identifying Unique Biomechanical Fingerprints for Rowers and Correlations with Boat Speed – A Data-driven Approach for Rowing Performance Analysis

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Abstract

Finding the best fit of rowers for a crew boat is a challenging task. Each rower has a unique technique and the ability to adapt this to a crew varies from person to person. Currently, subjective evaluations and qualitative measures are the main methods used to try to put the fastest crew together. To make the process more accurate and objective we introduce 177 performance metrics to quantify some of the measureable aspects of rowing technique. We then present two data-driven approaches to select the most relevant features that 1) make individual rower’s technique unique and 2) correlate most strongly to boat speed. The first approach uses sequential forward feature selection to identify the features that are most discriminative for individual rowers in crew boats. These features make the unique biomechanical fingerprint of each rower. We recorded a dataset with four world-class female rowers racing in double sculls in different crew combinations. We identified the “Finish Slip” as the most discriminative feature. A rower identification classifier based solely on this feature scored an accuracy of 74.6%. Applying one or two additional features this accuracy improved to 90.7% or 95.6% respectively. In a second approach we proposed linear regression analysis to identify the features that most strongly correlate to boat speed. For the given dataset, a subset of five performance metrics proved sufficient to build a linear model that predicts the boat speed with a root mean square error of less than 0.087 m/s.

9.1 Introduction

9.1.1 Motivation

Rowing is one of the oldest Olympic disciplines. To perform at the top level rowers must be physically strong and have excellent technique. Strength can be measured in off water setups with rowing ergometers and individual technical skills are often assessed on the water through competitions in small boats. In the case of sculling (two oars per person) tests are usually
carried out in single sculls (a one person rowing boat). Different athletes often have different ideal single sculling technique as they have different skill levels, body proportions and anatomy [15]. As such even athletes who perform at the top level are likely to have slightly different technique from one another.

In the Olympic regatta rowers compete not only in singles but also in crew boats of up to eight rowers. Apart from requiring a good strength and endurance base, rowers in crew boats must be able to synchronize their technique and timing with each other in order to achieve top results [27, 53, 109]. It is challenging to determine who the strongest and simultaneously most compatible athletes for a crew boat are.

Results show that crews made up of the best single scullers are often beaten by crews made up of rowers with worse individual performances. As Daniel Topolski, one of the most successful coaches of the annual Oxford-Cambridge boat race stated, “[t]he sum of a crew is greater than its parts” [82]. This has become a well-established saying and highlights that making a crew boat successful requires more than a group of individually good rowers.

The most common approach for finding ideal rowing crews within a pool of athletes is through test races. Coaches put crews together and organize races to determine which crew in which seating order performs best. It is usually not possible or practical to test all possible combinations due to time restrictions and the difficulty of ensuring comparable conditions between so many test races. Key challenges include changing weather conditions, differences in athletes’ required recovery time and ensuring that athletes perform to their best in each race.

Instead of testing all possible combinations, coaches currently decide which crews to test based on subjective evaluations and personal experience. The success of such an approach is highly based on the coach’s experience. This process is intransparent and often leaves the non-selected athletes with unanswered questions and a feeling that they were potentially unfairly overlooked.
A more systematic selection process would be to measure the biomechanical parameters of rowers and compute the features that describe their technique in order to determine which ones fit best together in terms of technique style and synchronicity. There are many possible metrics that could be extracted and some are already measured in leading high-performance rowing centers. One of the main challenges is to identify the most important of these available features. They should be descriptive and of key significance for a rower’s technique, meaning they remain different between individuals even when put together in a crew. These features should also be relevant for crew boats’ performances, meaning they should correlate with the boat speed.

9.1.2 Rowing Basics

The goal in rowing is to move the boat as fast as possible from start to finish, usually over the Olympic distance of 2000m. The boat travels backwards with the rower's back to the direction of movement. There are two sub-types of rowing: sweep-oar, in which each rower holds one oar and rotates either to the left or right side; and sculling, in which each rower holds two oars making symmetric movements with the left and right oar. The rower sits on a sliding seat allowing the body to move forwards and backwards and enabling the rower to further extend the stroke length. The rowing movement is cyclic and consists of two phases, the drive phase and the recovery phase. For the sake of simplicity this work focuses on sculling, however most of the methods can be applied to sweep rowing as well.

The drive phase starts in the forward most position, called the catch position (Figure 71a). The legs are bent, so that the shins are perpendicular to the water, the sliding seat is as close to the stern of the boat as possible, the upper body and shoulders are in front of the hips, and the arms and hands are fully extended, reaching out for maximal length. The blades are then placed into the water (Figure 71b). They are then driven through the water and the boat is accelerated by pushing back with the legs, moving the seat towards the bow, bending the arms and taking the upper body
Figure 71: Basic rowing stroke: The boat is moved backwards (from left to right). At the catch position (a) the blades are placed into the water (b). The boat is accelerated by pushing back with the legs and bending the arms until the rower reaches the finish position (c). The blades are extracted from the water and feathered (turned parallel to the water). Then the rower reaches forward, bending their legs and extending the arms to prepare for the next catch position (a). Then the cyclic movement continues with the next stroke.
back so that the shoulders are just behind the hips, while the back remains relatively straight. At the back most position, called the finish position (Figure 71c), the blades are extracted from the water and the recovery phase begins. During this phase, the rower prepares for the next stroke, moving the blade above the water to the catch position again. To minimize air drag and to increase boat stability, the blade is turned and moved into a feathered position above the water (Figure 71d). Finally, the blade has to be turned again so that it is at a right angle to the water, this is known as a squared blade. The cycle then starts again with the next drive phase (Figure 71a).

This stroke is repeated over and over again. A standard base training rate is 18-20 strokes per minute, while in 2km races it is generally between 32-37 strokes per minute. During the start, finish sprint and other strategic points in a race, the stroke rate can reach up to 43 strokes per minute.

The more force a rower applies the faster the boat is accelerated. However, muscle mass increases a rower’s weight, and the heavier a boat is the greater the drag factor. Therefore, the potential gain of boat speed through strength is limited and this is where rowing technique becomes essential. With more efficient technique the rower can manage to increase the boat speed with constant strength (and body mass). Not only does good technique maximize acceleration, it also minimizes deceleration [35]. Deceleration of the boat occurs mainly due to the forces applied to the footstretcher as the rower comes towards the catch. The deceleration is also caused by unstable boat movements, unsmooth oar movements and delays in placing the blade at the catch position.

In crew boats the ideal rowing technique is even more complex, since the individual rowers’ techniques have to fit with the other crew members’. According to Soper et al. this “ideal fitting” includes several aspects and successful scullers in crew boats show similar force profile characteristics [98]. Our work on the biomechanical rower fingerprint is based on the assumption that rowers in crew boats should move as synchronously together as possible. For the case of sculling, this is supported by many studies [27, 53, 109]. However, for sweep rowing some authors argue that
slightly opposite styles could also complement each other in a positive way [34, 93].

9.1.3 Related Work

Rowers are aiming to improve their technique to avoid injuries and to improve boat speed. In most cases, they rely on human coaches who accompany trainings and give feedback. Besides traditional tools such as stopwatches and high speed video cameras, there are multiple sensor-based approaches proposed and some are already available on the market. An overview of sensors for instrumented rowing boats is presented in Table 15.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnet</td>
<td>Seat</td>
<td>Reed switch to count strokes [74]</td>
</tr>
<tr>
<td>Impeller</td>
<td>Boat</td>
<td>Measure distance and speed relative to the water [63, 97]</td>
</tr>
<tr>
<td>GPS</td>
<td>Boat</td>
<td>Measure distance and speed relative to the shore [97]</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Boat</td>
<td>Measure stroke rate and interpolate boat movement [50]</td>
</tr>
<tr>
<td>Gyroscope</td>
<td>Oars, Boat</td>
<td>Measure oar angles [83]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Measure boat stability [44, 105]</td>
</tr>
<tr>
<td>Potentiometer</td>
<td>Oarlock</td>
<td>Measure horizontal oar angle [37]</td>
</tr>
<tr>
<td>Force sensor</td>
<td>Oarlocks, Foot stretcher</td>
<td>Measure force applied to oars [92]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Measure force applied on the foot stretcher [96]</td>
</tr>
<tr>
<td>Strain gauge</td>
<td>Oars</td>
<td>Measure bending force of oars [76]</td>
</tr>
<tr>
<td>Inertial meas-</td>
<td>Oars, boat</td>
<td>Measure oar and boat orientations and movements [42, 102]</td>
</tr>
<tr>
<td>urement units</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 15: Sensors used for rowing in on-water setups, adapted from [102]

Experienced rowing biomechanists are required to interpret the acquired data and generate benefits from it. Finding methods to automatically analyse the data and provide appropriate feedback for the coaches and athletes is an active field in research [20, 46, 96, 102].

Although rowers have their own styles [28, 29, 95, 102] coaches expect them to adjust their technique to achieve a common, efficient and syn-
chronous stroke when placed in crew boats. However, as Korndle et al. show, in practice rowers only manage to adapt some aspects of their technique for the crew. Regardless of the crew or boat class rowers are put in, they maintain their individual “signature” force angle profile, [65]. Through a more systematic analysis of a group of female rowers Galloway et al. were able to support this finding. They also found that some rowers’ movement patterns were more dominant than others in influencing the total boat speed [38].

Other studies explore the relative influence of rowers’ fitness, strength, physiological constitution, body measures, technique and boat and oar settings on boat speed [31, 52, 57, 64, 69, 96, 94].

Millward developed a model considering the fluid mechanics of the oar and verified it with rowing performance data [72]. He identified the shape of the rowing force curve and the proportion of recovery time in the total stroke as important factors for the boat speed. Sanderson and Martindale developed an equation to describe the boat speed as a function of the movement of the rower’s center of mass and the applied force [84]. To increase the efficiency, the authors suggest building lighter boats, increase the blade area of the rowing oar and finding an ideal stroke rate depending on the rower’s body mass.

Medical and physiological determinants for boat speed are explored in clinical studies. Baguet et al. found that supplementation of β-alanine is highly effective in increasing the performance of elite rowers. After a 7-week study his control group improved an average of 4.3 seconds more than the placebo group [22]. Ingham et al. measured the oxygen intake during ergometer rowing. The best correlation to the resulting performance was the applied power during maximum oxygen consumption [54].

Secher and Vaage present a mathematical model for forecasting the racing times of male and female rowers depending on body mass. They found that heavyweight rowers had a 2.6% advantage in comparison to lightweight rowers. This value was supported by on-water results [87].

To sum up, most of the published approaches that present dependencies and influences of input factors on the boat speed are based on biomechan-
ical models, trying to cover the causal dependencies and interactions as accurately as possible. These deductive approaches are advantageous in the sense that models can be built based on them and validated using theoretical knowledge and simulations. They can be generalized from because assumptions and limitations are usually known. The main disadvantage is the complexity to which these models can grow if they try to represent reality as completely as possible. These models usually require dozens of input parameters and some of them can hardly be measured or estimated.

Data-driven approaches like regression models have the potential to address this drawback. They are built in an inductive way and based on the input parameters that can be measured in real-life settings. For example, Perl & Baca introduced the application of neural networks to performance analysis in rowing and managed to identify instabilities in the movement patterns [78]. The main drawback of these inductive methods compared to approaches based on physical models is the missing proof of causality. In fact, they identify correlations solely based on available data, this can be a sign for causal dependencies but not a proof. More data and domain-specific knowledge is needed to confirm dependencies, identify limitations and to explore how the model can be generalized, for example for other boat classes.

9.1.4 Contribution

More and more sensors and measurement systems that can be used to obtain quantitative data of rower’s performances on the water are becoming available. To make this available data beneficial for rowers and coaches, this work mainly focuses on the post-processing part and introduces methods for meaningful data analysis.

We extend the state of the art in the following respects:

**Performance Metrics.** To describe the rowing technique quantitatively, we introduce 37 boat-specific, 28 oar-specific and 112 crew-specific features. These are the base of our data-driven performance analysis.
Biomechanical Fingerprints. We propose and compare three different machine-learning methods to identify the most discriminative features for a group of rowers. We demonstrate how this approach can support coaches towards a more systematic approach for finding the best-fitting team for a crew boat.

Boat Speed Model. We suggest a linear model to describe the dependency between boat- and oar-specific performance metrics as input and the boat speed as output parameter. The number of necessary coefficients and their values are identified with a step-wise linear regression analysis.

Proof of Concept. We carry out an experiment with four elite rowers performing races in different crew combinations within a time period of six days. Data has been recorded with commercial sensor systems. In a post-processing step, performance metrics were calculated, and our proposed methods are applied and results discussed.

9.1.5 Paper Organization

The second section explains how meaningful performance metrics can be extracted from raw sensor data and introduces oar-, boat- and crew-specific metrics. The third section, “Experiment Setup” introduces the measurement system we used to instrument the rowing boats and the experiment design applied to collect data from different crew combinations. The following two sections explain our methods and the results we obtained using the data from our experiment. The section “Analysis and Discussion” analyses the results and outlines possible interpretations of them. Limitations are discussed in the next section and the final section draws conclusions and provides an outlook.

9.2 Performance Metrics for Individual Rowers and Crews

As outlined in the introduction, the general idea of good rowing technique is well-established [35]. For most technical aspects of rowing, there are
rough guidelines rather than exact quantifiable and measureable targets. However, to enable comparison of rowers and crew combinations through data-driven approaches we need quantitative measures, which can be obtained with mobile on-boat sensor systems. It is important that the selected set of measures contain as little redundancy as possible. In the first of the following two sub-sections we introduce performance metrics that can be applied to all boat types. These ones include:

- **Boat-specific features**: These features describe the movements of the boat. These features have identical values for all crew members and quantify the effects of the crew as a whole.
- **Oar-specific features**: These features describe the movement of an individual rower’s oar. In crew boats these features usually have different values for each person.

In the second sub-section we present additional features that are only available for crew boats. They quantify the crew synchronicity based on the oar-specific features of all crew members. All features are calculated once per stroke.

### 9.2.1 Performance Metrics for all Boat Types

In collaboration with Olympic-level rowing coaches and leading rowing biomechanists we define 37 boat-specific features and 28 oar-specific features.

#### 9.2.1.1 Boat-Specific Features

Boat-specific features mainly describe the boat behavior such as its acceleration, speed and instability. Boat instability is quantified by deviations of the boat orientation in three dimensions. The corresponding angles are visualized in Figure 72. The complete list of the proposed boat-specific features can be found in Table 21 (Appendix).
9.2.1.2 Oar-Specific Features

Oar-specific features describe the movement of the rowing oar, such as the amplitude of movement, the timing and the force applied. For the sake of simplicity this work, which focuses on sculling, only evaluates the rowers’ bowside oars. The definitions of the most relevant features are shown in Figure 73.

Similarly to the boat-specific features, the oar-specific features are also stroke-based, with one set of features describing one rowing stroke. They are calculated separately for each crew-member. The complete list of proposed oar-specific features can be found in Table 22 (Appendix).
9.2.2 Additional Performance Metrics for Crew Boats: Synchronicity Measures

The first step computes the oar- and boat-specific features introduced in the previous sub-section. In the second step we add additional features that describe the crew’s interaction and synchronicity. For a crew boat with $N$ rowers and $k$ oar-specific features per rower, we define $(N+2)k$ crew-specific features. The full set of proposed crew-specific features is described in Table 16.

<table>
<thead>
<tr>
<th>Names of features</th>
<th>Description</th>
<th>Number of features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diff</td>
<td>The difference of each rower’s features compared to the rower in the stroke position is calculated</td>
<td>$(N-1)k$</td>
</tr>
<tr>
<td>Min</td>
<td>The minimum value of each oar-specific feature within the crew is calculated</td>
<td>$k$</td>
</tr>
<tr>
<td>Max</td>
<td>The maximum value of each oar-specific feature within the crew is calculated</td>
<td>$k$</td>
</tr>
<tr>
<td>Mean</td>
<td>The mean value of all oar-specific features within the crew is calculated</td>
<td>$k$</td>
</tr>
</tbody>
</table>

Table 16: Descriptions of crew-specific features. These features describe the crew interaction and synchronicity in crew boats.
9.3 Experiment Setup

9.3.1 Mobile On-Boat Measurement System

The minimum measurement setup to compute all proposed performance metrics consists of angle and force sensors on each rowing oar or gate as well as a GPS, accelerometer and gyroscope measurement module mounted on the boat. We decided to combine two commercially available systems:

- Boat-mounted sensor: A MinimaxX module (Catapult Sports, Australia) is attached to the boat’s stern. It measures GPS, 3-axes accelerometer and 3-axes gyroscope data with a sample frequency of 100Hz.
- Oarlock integrated sensor: The PowerLine Rowing Instrumentation system (Peach Innovations Ltd., United Kingdom) is an instrumented oarlock that enables force and angle measurements with a sampling frequency of 50Hz.

The overall setup is depicted in Figure 74. Both devices work independently and save the data to internal memory. After the experiment both memories are read out and a semi-automated method is used to synchronize and merge the data.

Figure 74: The overall measurement setup for a double scull rowing boat is shown in (a), the boat sensor is attached to the stern of the boat (1), the two rowing oar sensors are integrated into the oarlocks (2). Close-ups of the boat module and oarlock module are shown in (b) and (c).
9.3.2 Test Races for Data Collection

For the data recording we recruited four Olympic-level female rowers (A, B, C and D) and equipped two double sculls with the described mobile measurement system. During a 6-day rowing camp, the athletes performed a race over 2000m every other day. The days in between were used for training and recovery (Table 17). This way, all six possible crew combinations were tried out and in total 1459 rowing strokes were recorded during the races.

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Day 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boat 1</td>
<td>Recovery and training</td>
<td>B, A</td>
<td>Recovery and training</td>
<td>B, D</td>
<td>Recovery and training</td>
<td>C, B</td>
</tr>
<tr>
<td>Boat 2</td>
<td>C, D</td>
<td></td>
<td></td>
<td>C, A</td>
<td></td>
<td>D, A</td>
</tr>
</tbody>
</table>

Table 17: During the 6-day data collection all double combination of the four rowers (A, B, C, D) were measured in race conditions

9.3.3 Feature Calculation

The complete feature calculation processing chain is depicted in Figure 75. The recorded continuous data was segmented into strokes, using a peak-detection algorithm on the boat acceleration data. For each of the 1459 recorded rowing stroke cycles, we computed 37 boat-specific features and 56 oar-specific features (28 for each rower), totaling 93 unfiltered features per stroke.

To filter for noise effects and outliers, we segmented the races in approximately 50-meter intervals and combined strokes within these segments. For each segment we computed the average and the standard deviation for each feature of the strokes within the segment. In total, for all six races, we received 248 race segments, each with 74 filtered boat features and two times 56 filtered oar features (Figure 75a). Based on the 56 filtered oar-specific features (28 averages and 28 standard deviations) for each rower, we computed 224 crew-specific features (Figure 75b).
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

Figure 75: Feature calculation processing chain for double scull. (a) describes the calculation of the filtered boat and oar features, (b) describes the continuation for calculating the crew features.
The final database consists of 248 race segments, each with 410 features (74 boat-specific, 56 oar-specific for each rower, 224 crew-specific). In the following analysis, we only consider these filtered features and we use the following naming convention: the original feature names (according to Table 21 and Table 22) refer to the averaged values. The standard deviations are named with the prefix “Std-” following the original features’ names. The crew-specific features use the additional prefixes “Diff-”, “Min-”, “Max-” and “Mean-”, as taken from the definitions in Table 16.

9.4 Methods

The data analysis was divided into two parts (Figure 76). In the first part we analyzed which features were the most discriminative for individual rowers even when put together in crew boats. The identified set of features is most suitable for identifying differences in rowing styles, it is the unique biomechanical fingerprint for rowers.

![Diagram](image)

**Figure 76:** Data-driven support for crew selection consists of two analyses, (a) identifies which features are most discriminative for individual rowers and (b) ranks the features considering their impact on the boat speed.

The second part of the data analysis identified which biomechanical features of crew boats correlated most strongly with boat speed and therefore require particular attention when evaluating how well a crew fits together.
9.4.1 Biomechanical Fingerprint Identification: Wrapper-Based Feature Selection

9.4.1.1 Problem description and requirements

As described in the previous section, we generated 74 boat-specific and 56 oar-specific features. In this section we want to identify which features out of these 130 proposed features make up the rower’s biomechanical fingerprint. We define the following requirements these fingerprint features should fulfil:

1. **Uniqueness**: The selected feature subset should be most discriminative for each rower. This means by knowing these features, the rower can be identified. The selected features are the ones in which any two rowers of our dataset are most different from each other.

2. **Constant**: The selected features do not depend on the crew partner. For each rower, the values of the selected features stay within a specific and individual range, even when put together with other rowers.

9.4.1.2 Our approach

The problem of finding the most discriminative features out of a given pool of features is well-known in the machine learning community. The overview of our approach is depicted in Figure 77. The input data are the instances for the 130 considered features. Since each of the 248 race segments contains two sets of oar-specific features, one for each of the two athletes in the boat, there are in total 496 data instances available. The first step of our iterative process (Figure 77) is to generate a subset of features according to a search strategy. Then, this subset is evaluated according to an optimization criterion. These two steps are repeated over and over again until a stop criterion is achieved and the feature subset with the best evaluation value is outputted. The stop criterion can be a certain threshold
of the evaluation value or the end of the implemented search strategy. In our work, the latter is the case.

Feature subset generation. A full test of all possible subsets of features would require testing $2^{130} \approx 10^{39}$ possibilities. To reduce the number of required iterations, we implemented sequential forward feature selection as search strategy. In a first step, all possible subsets containing only one single feature are evaluated. The second step considers the best subset from the first step and evaluates all possibilities of extending this subset with a second feature. The extended subset with the best evaluation score makes it through to the third step and so on. In each step, the winning
subset of the previous step is extended by one additional feature. This search strategy ends as soon as a predefined threshold accuracy is reached, a predefined number of features is selected or after all features are selected. In our case the maximal number of tested subsets is $131 \cdot \frac{130}{2} = 8515$. Compared to the full search, this search strategy saves computational resources while proving good results in many applications [56], however it does not assure to find the theoretically best possible result.

**Feature subset evaluation.** To evaluate a given subset of features there are filter and wrapper approaches. Filter methods are based on statistical characteristics; they evaluate the given subset for example according to its dependencies, relevance or redundancy [77]. Wrapper methods evaluate the given data according to the accuracy a classifier can correctly classify it. Wrapper methods are usually computationally more expensive than filter approaches. Feature subsets selected by wrappers are optimized for the specific classifier used during the selection process. In this work we used wrappers, because they usually outperform filters when it comes to prediction accuracy using the classifiers they are optimized for [113]. A schematic overview of our wrapper-based feature subset evaluation is shown in Figure 78. We used 3-fold cross-validation, which means the evaluation is done in three parallel processes. Each process uses two thirds of the 496 input data sets to train the classifier (i.e. build the model), the other third is used to test the model and calculate the classification accuracy. The mean value of all three accuracies is the evaluation output for the given feature subset.

**Classifiers.** In general, classifiers are used to identify categories based on the input data. In our case, the input data is the subset of feature values which was calculated for the race segments. The ‘category’ which has to be inferred from this input data is the athlete ID. Working with classifiers involves two steps: Building the model and applying it. The first step, also known as training phase, considers input datasets as training data and outputs the model. The second step applies the model to the test datasets. For each test dataset, the model outputs a predicted athlete ID, which is compared to the actual athlete ID. The accuracy is calculated as the share of correctly predicted athletes:
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

\[
\text{accuracy} = \frac{\text{#correctly predicted athlete IDs}}{\text{#total number of predictions}} \cdot 100\%
\]

Figure 78: Feature subset evaluation with classifier (wrapper approach) and three-fold cross-validation.

In this work we use three state of the art classifier algorithms:

**k-nearest neighbors (kNN):** This is a very basic and transparent classifier. For each classification result it is easy to trace back which learning datasets are responsible for the result [16]. We chose k=4.

**Support Vector Machines (SVM):** This is the most popular classification algorithm, scoring best results for most applications. The main disadvantages are the danger of overfitting and the computationally expensive
process when building the model [30]. We used SVM with radial basis functions.

**Random forest (RF):** A high number of decision-trees are generated. The majority vote of these sub-classifiers determine the classifiers output. This way, even complex cluster boundaries can be represented while overfitting is avoided [73]. We used \( N=300 \) trees.

### 9.4.2 Correlations with Boat Speed: Linear Regression Analysis

#### 9.4.2.1 Problem description and requirements

We want to find out which of the proposed features most strongly correlate with the boat speed. This subset of features should 1) contain as few features as possible and at the same time it should 2) enable the prediction of the boat speed as accurately as possible.

Besides the identification of the most strongly correlated features, we want to determine how strong and in which direction (positively or negatively correlated) the dependencies are.

#### 9.4.2.2 Our approach

The feature selection and classifier approaches presented in the previous sub-section are designed to predict qualitative and discrete labels such as the athlete IDs. In contrast, the boat speed is a continuous quantitative output, thus we need another approach to model and predict it. We decided to use linear regression analysis because the resulting model defines transparently which features are correlated; it also calculates weight factors to describe the strength and direction. According to Zou et al. these weight factors are more suitable to assess the strength of the relationships in the data than correlation coefficients [114]. The overall process is depicted in Figure 79 and is described in the following paragraphs.
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

Figure 79: Feature subset selection with linear regression. Input values are the features of the current (t) and the previous stroke (t-1). Output values are the features and corresponding weight factors that are used to describe the boat speed.

We expect that the boat speed of race segment $i$ does not only depend on the feature values of the same race segment, but also on the previous race segment $i−1$. For this reason, the feature values of each previous 50m race segment were used to increase the dimensionality of the input feature space. These features are named with the additional prefix “Last-”. On the other hand, we excluded all features which are calculated based on boat velocity (e.g. “Distance per stroke”) because their dependency on the boat speed is obvious and therefore not interesting. All features are scaled to ensure values between -1 and 1.

As ground truth value for the boat speed we used the speed output of the boat-mounted sensor. This is calculated based on GPS speed and boat accelerometer data as proposed by Davey et al. [32]. For each race segment $i$, the average $v_i$ of this measured velocity was calculated and summarized in vector $\mathbf{v} = (v_i)$. 

\[ W_1, W_2, \ldots, W_N \]
For a given (sub)set of $N$ features, each column of the data matrix $X \in \mathbb{R}^{K \times N}$ represent one feature, the rows are the $K = 242$ instances of the features. We assume a linear relationship between feature values and the predicted boat speed $v_p$ (output):

$$v_p = X \cdot w$$

The weight factors $w$ are calculated using the least squares approach [66, 110]:

$$w = (X^T \cdot X)^{-1} \cdot X^T \cdot v$$

This method minimizes the root mean square error (RMSE) between the predicted velocity and the measured velocity [18]:

$$RMSE = K^{-0.5} \cdot \|e\|_2 \text{ with } e = v - v_p$$

We wanted to generate a ranking of the features which are most strongly correlated with the boat speed. For this task, we implemented a stepwise linear regression, which increases the number of features $N$ following a sequential forward selection strategy, similar to the presented wrapper approach described before and depicted in Figure 77. The evaluation criterion is the RMSE.

To ensure the ranking and the calculated weight factors to be as representative as possible, we considered the full set of $K = 242$ instances of the data (no cross-validation) for this feature selection/ranking step. However, for the sake of statistical correctness, the RMSE values which are used for further calculations and are given in the result tables are calculated using 10-fold cross-validation.

With the generated ranking we can determine the minimal number of features $N$ needed to achieve a ‘good fit’, which our collaborating coaches and biomechanists defined as a RMSE of less than 35% of the measured velocity’s standard deviation.
9.5 Results

9.5.1 Biomechanical Fingerprint Identification

The five top-ranked features and the corresponding average accuracies (see section 9.4.1) are listed in Table 18. These accuracies are also visualized in Figure 80.

<table>
<thead>
<tr>
<th>Rank</th>
<th>kNN</th>
<th>RF</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ang Finish Slip  74.6 %</td>
<td>Ang Finish Slip  67.3 %</td>
<td>Ang Finish Slip  63.5 %</td>
</tr>
<tr>
<td>2</td>
<td>Ang Drive Accel Point  90.7 %</td>
<td>Ang Drive Accel Point  89.3 %</td>
<td>Yaw Recov Yaw Range  86.7 %</td>
</tr>
<tr>
<td>3</td>
<td>Handle Vel Drive Max   95.6 %</td>
<td>RFD Peak       94.0 %</td>
<td>Ang Drive Accel Point  91.7 %</td>
</tr>
<tr>
<td>4</td>
<td>Std-Ang Catch         96.6 %</td>
<td>Handle Dist    96.6 %</td>
<td>RFD Peak       95.6 %</td>
</tr>
<tr>
<td>5</td>
<td>Ang Catch             97.4 %</td>
<td>t Max Force    97.2 %</td>
<td>t Drive       96.2 %</td>
</tr>
</tbody>
</table>

Table 18: Rower’s biomechanical fingerprint: Top five most discriminative features for identifying individual rowers. The rankings are obtained by sequential forward feature selection with three different classifiers: k-Nearest-Neighbor (kNN), Random Forest (RF) and Support Vector Machines (SVM). The percentages indicate the average achieved accuracy of each classifier when using only the top-ranked feature, the top two features, the top three features, the top four or top five features.

Figure 80: Visualization of how accurately a rower can be identified with a defined biomechanical fingerprint. The more features that are allowed in the fingerprint, the more accurately the rower can be identified. The results are plotted for three different classifiers (kNN, RF, SVM).
The feature “Ang Finish Slip” is ranked as the most discriminative feature in all tested approaches. The feature “Ang Drive Accel Point” is ranked as second or third in all tested approaches. The distributions of the values of these two features and some of their statistical properties are illustrated in Figure 81.

Figure 81: The boxplot (a) shows the statistical parameters of the “Finish Slip”, the most discriminative feature for rower identification. The boxplot (b) shows the distribution of the feature “Ang Drive Accel Point” which is ranked second or third, depending on the used classifier.
9.5.2 Correlations with Boat Speed: Linear Regression Analysis

For the total database of $K = 242$ race segments, we received 79 different boat speed values, ranging between 4.37m/s and 5.6m/s. The mean boat speed is 4.75m/s and the standard deviation is 0.25m/s. The distribution of the boat speed values is shown in Figure 82.

![Figure 82: This histogram shows the distribution of boat speed values in our recorded dataset](image)

The dependency between the number of features and the resulting RMSE is visualized in Figure 83.

![Figure 83: Dependency between number of features used for the linear regression and the resulting root mean square errors (RMSE) between predicted and measured boat speed.](image)
The graphic shows that $N = 5$ features are needed to achieve the defined goal regarding the resulting RMSE. The selected features for this case and the corresponding weight factors are summarized in Table 19. A visual comparison of the measured and the predicted boat speed based on this model is shown in Figure 84.

<table>
<thead>
<tr>
<th>Rank ($i$)</th>
<th>Feature ($x_i$)</th>
<th>Weight ($w_i$)</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Max-Handle Vel Drive Max: Maximal oar handle velocity during drive phase, maximal value of both rowers during the current 50m race segment</td>
<td>2.79</td>
<td>0.124</td>
</tr>
<tr>
<td>2</td>
<td>Last-Min-Handle Vel Recov Ave: Average oar handle velocity during the recovery phase, minimal value of both rowers during the previous 50m race segment</td>
<td>-1.06</td>
<td>0.098</td>
</tr>
<tr>
<td>3</td>
<td>Last-Std-Accy Recov Min: Minimal value of transversal boat acceleration during recovery phase, standard deviation of these values during the previous 50m race segment</td>
<td>0.15</td>
<td>0.093</td>
</tr>
<tr>
<td>4</td>
<td>Last-Max-Power Drive Ave: Average power applied by the rower to the oar handle in propulsive direction, the maximal value of all strokes during the previous 50m segment from both rowers.</td>
<td>0.56</td>
<td>0.090</td>
</tr>
<tr>
<td>5</td>
<td>Last-Mean-Handle Vel Drive Ave: Average oar handle velocity during drive phase, mean value of both rowers during the previous 50m race segment</td>
<td>1.17</td>
<td>0.085</td>
</tr>
</tbody>
</table>

Table 19: Top five features and their corresponding weights for linear regression model for boat speed prediction. The last column indicates the root mean square error (RMSE) value when using only the first, the first two, three, four or all five features in the model.
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

9.6 Analysis and Discussion

9.6.1 Biomechanical Fingerprint Identification

With the help of machine learning approaches we showed that our proposed features are discriminative enough to identify the individual rowers in our experiment. Out of all 130 features, the “Finish Slip” is the most discriminative feature for all three tested feature selection methods. By knowing this single value, the corresponding rower can be identified with an average accuracy of 74.6%. Using the top three features, the classification accuracy scores 95.6%. None of the boat-specific features ranked within the top-five features to discriminate a rower. Rower’s individual characteristics can be found primarily in their oar movement rather than their impact on the boat drive or stability.

Figure 85a depicts the values of the two most discriminative features. One point in the plot corresponds to one rower during one race segment. The four colors indicate the athlete identities (A, B, C or D). The six different shapes of the point markers correspond to crew combinations. For example, squares are available in red color and in black color. These points correspond to the race segments in which rower A (red) and rower C (black) were rowing the double together.

Figure 84: Comparison between predicted and measured boat speed, complete data set consisting of 6 races by different crews.
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

(a) Finish Slip vs. Ang Drive Accel Point [normalized]

(b) Finish Slip vs. Ang Drive Accel Point [normalized] with data clusters labeled A, B, C, D.
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

Figure 85: The scatter plot (a) shows the distribution of the two most discriminative features. One marker corresponds to averaged features of one rower during one race segment. Different colors indicate different rowers. Same marker shapes indicate same crew combinations. (b) indicates the 80% confidence ellipses forming clusters of the individual rowers. (c) marks three sub-clusters of rower D. Each sub-cluster corresponds to rower D’s technique when rowing in three different crews. Each cluster in (d) correspond to one crew and considers all strokes from both crew partners. The more compact the clusters are, the more similar the two crew partners are rowing.
Figure 85b includes covariance error ellipses [55, 100]. These ellipses represent the two-dimensional 80% confidence intervals in which the features for each rower can be found. It shows that each rower occupies a dedicated area and forms an individual cluster which only partly overlaps with other rowers’ clusters. For each rower, the values of the two features are variable but they stay within individual ranges. This illustrates the discriminative nature of these two features for each rower.

Within each of these four clusters three sub-clusters can be identified. For rower D (green), the sub-clusters are marked with green stars, green diamonds and green circles. These sub-clusters are highlighted with the corresponding 80% confidence ellipses in Figure 85c. Each of these sub-clusters corresponds to one crew combination the rower D was part of. The size of the sub-clusters illustrate the rower’s consistency: The bigger the area of one of these sub-clusters is, the more inconsistent the rowing technique of the corresponding rower was when racing in the corresponding crew combination [78]. For example, the technique of rower D was most consistent when rowing together with rower C. Besides looking at the size of the sub-clusters, we can also find information considering their positions and overlaps. This distribution is a measure for the rower’s adaptability: If the sub-clusters of one rower are close to each other or even overlapping, this indicates a dominant rowing technique or limited adaptation capabilities of the rower. Rowers with sub-clusters which are apart from each other show that they adjusted their technique under the influence of the other rower in the crew. The sub-clusters from rower A are the least spread-out ones. This rower kept her technique most constant, also when rowing together with other crew partners.

For each rower, the corresponding sub-clusters are mainly spread out on the y-axis. This means the main adjustments were made concerning the “Ang Drive Accel Point” feature, only rower D managed to vary the “Finish Slip” parameter as well.

Clusters from rower B and D have the largest overlap (Figure 85b). This means these two rowers have the capability to perform similar rowing technique according to the two considered features. However, when these two rowers are sitting together in the boat, they do not use this technique,
the two corresponding sub-clusters (blue diamonds and green diamonds in Figure 85a) are not overlapping. Clusters from rower A and B as well have an overlap in Figure 85b. In contrast to the previous example, these two rowers not only have the capability to perform similar technique, they also actually apply this common technique when they row together. This is visualized by the overlap of the corresponding two sub-clusters (blue crosses and red crosses) in Figure 85a.

In Figure 85d each pair of sub-clusters is merged and their corresponding confidence ellipses are illustrated. Each of these six clusters visualizes one crew combination and includes all strokes of both rowers sitting in the boat. When compared to the others, the cluster BA is the most compact one. This again illustrates, that these two rowers are most similar and consistent over time concerning the two considered features. This combination also achieved the fastest time over the 2000m race distance. The size of each of the six clusters is calculated and compared to the achieved race time in Table 20. In each race, the winning boat also scored a smaller cluster size.

<table>
<thead>
<tr>
<th>Race 1</th>
<th>Race 2</th>
<th>Race 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crew</td>
<td>Time</td>
<td>Cluster size</td>
</tr>
<tr>
<td>BA</td>
<td>6:57.51</td>
<td>8.055</td>
</tr>
<tr>
<td>CD</td>
<td>7:00.06</td>
<td>20.073</td>
</tr>
</tbody>
</table>

Table 20: Summary of achieved 2000m race times (in minutes) and corresponding cluster size (in pixels) for each crew combination. Cluster sizes are calculated from Figure 85d, they are a measure on how different the rowing technique of both crew partners is.

9.6.2 Correlations with Boat Speed

The proposed linear model needs $N = 5$ features as input variables to be able to predict the boat speed with a root mean square error of less than 35% of the standard deviation of the measured boat speed. In Figure 84 it can be seen that the highest error usually occurs during the start phase of
the race, where rowers’ technique is usually different compared to the rest of the race. Measured velocity peaks during the middle phase of the race are most probably due to changed environment conditions such as wind or bumpy water. These external influences are not considered in our regression model and therefore the prediction does not include these peaks.

We used the identified correlations as well as their weights as starting points for discussions with rowing biomechanists to discover and explain potential causal dependencies:

Four out of the top five features (Table 19, features 2-5) are metrics that were measured during the previous race segment. This indicates that the average boat speed during one 50m race segment correlates highly to what happened during the previous 50m race segment. This suggests that there is a reaction time of several meters until changes in the oar or boat movement impact the boat speed. This inertia can be explained by the crew and boat mass of 160kg to 180kg.

All five selected features are boat-specific (Table 19, feature 3) or crew-specific (Table 19, features 1, 2, 4 and 5). None of the individual oar-specific features falls within the most correlated features. The experiment was not able to determine whether a particular seat in the boat, in this case bow or stern, correlates more strongly to the boat speed than the other.

The maximal value the handle speed reaches during the drive phase of the stroke is the most strongly correlated feature to boat speed (Table 19, feature 1). Assuming the blade is fully in the water, a higher handle velocity leads to more boat acceleration and therefore the positive correlation factor with the boat speed is consistent with coaching expectations. Similar explanations apply for the power applied to the oar handle (Table 19, feature 4) and the average handle velocity (Table 19, feature 5). These two features are the fourth- and fifth-ranked features and also correlated positively with the boat speed.

The second-ranked feature is based on the average oar handle velocity during the recovery phase (Table 19, feature 2). The correlation factor of this feature is negative, meaning the model predicts the faster the handles are moved during the recovery phase, the slower the boat speed. This is in
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

line with coaching literature [98], which teaches that the rower should move slowly to the catch position relative to the speed of the drive phase. The slower movement is especially important at the end of the recovery phase in order to enable a smooth transition to the next drive phase.

The third-ranked feature is the standard deviation of the transversal boat acceleration during the recovery phase (Table 19, feature 3). This feature is a measure for the boat instability. The correlation factor is positive. However, the data-driven method cannot decide whether a) higher instability causes higher boat speed, or b) higher boat speed causes higher instability. Biomechanical models and coaching literature suggest that option b) is the most likely [15, 37, 44, 92]. Higher boat speed leads to more unintentional boat movements, which increases drag factor.

The standard deviation of transversal boat acceleration (Table 19, feature 3) is the only boat-specific feature in the top-five features, the others are all crew-specific. According to Loschner et al. variations of boat orientations, which is another indicator of instability, can largely be explained by different rowing styles, skills and experience levels [70]. Thus, this boat-specific feature can probably be substituted by a combination of more fine-grained oar- or crew-specific features that more specifically explain the causes of the boat instabilities.

9.7 Limitations

We are aware that the described approach has several limitations.

**Obtrusiveness.** The boat measurement system is designed to be as unobtrusive as possible, however the instrumented boat is not physically identical to the usual uninstrumented one, and therefore it cannot be fully assured that the boat behavior is unchanged. Additionally, rowers might be psychologically impacted by knowing that their movements are being recorded and consequently they might row differently. However, similar sensor setups have been found unobtrusive in related studies [102].

**Measurement errors.** We have not validated the error involved by the used measurement systems. According to the manufacturers, the force sensor is
accurate to 2% of full scale (1500N), the oar angle sensor’s accuracy is better than 0.5°, the boat speed and accelerometers are accurate to 2%. However there might be additional inaccuracies caused by mounting errors and misalignments.

**Generalization.** The number of rowers and measurements we used is limited and the measured group of rowers is not representative. Thus, the specific results cannot be generalized. To answer analogical questions for other rowers, the presented methods have to be applied to these rowers’ data. The goal of this work is to introduce generalizable methods, rather than to provide statistically relevant data for a representative group of rowers.

### 9.8 Conclusion

Each rower has a different rowing technique and different capability to adjust their technique to be compatible for a crew boat. In collaboration with elite-level rowing coaches and biomechanists we introduce quantitative performance metrics that describe crucial parts of rowing technique and which can be measured using unobtrusive mobile sensor systems in rowing boats. We implemented three different classifiers and performed sequential forward feature selection to identify the features that are most unique for each rower. These features make up the rower’s biomechanical fingerprint and are relevant for identifying the best-fitting rowers for crews. We collected data from four world-class female athletes while they raced against each other in different crew combinations. We applied the described method to this dataset. The “Finish Slip” feature, which describes the rower’s efficiency at the end of the rowing stroke, turned out to be the most discriminative feature. Our proposed k-nearest neighbor classifier outperformed the random forest and support vector machine classifiers in terms of rower identification accuracy. It was able to identify 74.6% of the rowers correctly solely based on this single feature which requires only oar sensor modules. Applying one or two additional features this accuracy improved to 90.7% or 95.6% respectively, however these features require an additional boat sensor to acquire boat accelerations. The two rowers
with the best similarities regarding the two most discriminative features also scored the best time in comparison to all the other combinations within the group and later received an Olympic medal.

In the second part of this work, we showed how a linear regression model can be used to identify correlations between rowing features and boat speed. Our goal was to achieve a root mean square error below 0.087 m/s which is 35% of the boat velocity’s standard deviation. By gradually increasing the number of features, we found that five features were sufficient for the given dataset to reach this goal. The results of this data-driven approach suggest that boat velocity is mainly correlated to oar-specific input features and that there is a time delay of about 50 meters before input variances fully effect the output. The corresponding weight factors for these five input parameters were determined with the least-squares optimization algorithm. We also outlined that the statistical dependencies we found were consistent with the experiences of rowing biomechanists and coaches, and we discussed potential causal relationships for these dependencies.

9.9  Outlook

In future studies we plan to increase the number of sensors to extend the number of available performance metrics. Although the number of features presented in this work is sufficient for achieving classification accuracies of >95%, a broader set of features could offer new insights. This way, the results of the proposed data-driven approaches can be more fine-tuned and features describing boat-movements can be broken down into actual causes. For example instead of features describing the overall oar movement, measurements of the leg, upper body and arm movements can be included.

Further studies will also add more data to the database and this way makes the results statistically more relevant and easier to generalize from. Specifically, we are interested in applying and adapting the methods for male rowers, bigger crew boats, lightweight rowers and sweep rowing. Additionally, time-dependency can be considered in order to account for anomalies
due to sprint phases during races or different degrees of fatigue during training.

The presented crew selection example is based on the assumption that crew members should row as synchronously as possible. Although our recorded speed data supports this assumption for sculling, it would be interesting to investigate if and how a crew could benefit from complimentary rowing movements in sweep rowing.

We would like to further explore whether the position that a rower is seated in within a crew influences his/her biomechanical fingerprint. Based on qualitative experiences in related works, we expect rowers’ behavior and their effect on the boat to differ depending on the position they sit in within the crew.

Further research concerning data-driven boat speed dependencies is ongoing. Instead of linear models with calculated features as input, we want to test non-linear models and/or use raw data as input.

Finally, the vision is to combine both presented methods, the biomechanical fingerprint identification and the boat speed correlation, to find an overall crew efficiency measure that identifies the rowers within a group that best fit together and generate the features that most increases the boat speed.

Acknowledgments

The authors thank all rowers who participated in the studies and pre-studies, and the collaborating coaches for their valuable time and feedback. Further thanks go to Rosa Brown from www.topproofreading.com for editing and proofreading this work.
### 9.10 Appendix

<table>
<thead>
<tr>
<th>Names of features</th>
<th>Description</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stroke Rate</td>
<td>Number of strokes per minute</td>
<td>Boat-acceleration</td>
</tr>
<tr>
<td>Vel Max, Vel Min, Vel Ave, Vel Range</td>
<td>Maximum, minimum, average and range of boat velocity during one stroke</td>
<td>GPS, boat acceleration</td>
</tr>
<tr>
<td>Dist/Stk</td>
<td>Distance in meters the boat travelled during one stroke</td>
<td>GPS, boat acceleration</td>
</tr>
<tr>
<td>Vel Catch, Vel Finish</td>
<td>Boat velocity at the beginning (catch position) and the end (finish position) of the drive phase</td>
<td>GPS, boat acceleration</td>
</tr>
<tr>
<td>t Catch Lost, Vel Catch Lost</td>
<td>Time interval between reaching the catch position and placing the blade into the water; and amount of velocity the boat lost during this delay.</td>
<td>GPS, boat acceleration</td>
</tr>
<tr>
<td>Acc Drive Min, Acc Drive Max</td>
<td>Minimal and maximal boat acceleration (propulsive direction) during the drive phase. The same features are extracted for the other two acceleration axes (transversal and vertical acceleration).</td>
<td>boat acceleration</td>
</tr>
<tr>
<td>Acc Recov Peak</td>
<td>Value of highest boat acceleration peak (propulsive direction) during recovery phase</td>
<td>boat acceleration</td>
</tr>
<tr>
<td>t Recov Decel</td>
<td>Length of time interval the boat is decelerating for during recovery phase</td>
<td>boat acceleration</td>
</tr>
<tr>
<td>Accy Recov Min, Accy Recov Max, Accz Recov Min, Accz Recov Max</td>
<td>Minimal and maximal boat acceleration (transversal and vertical acceleration) during the recovery phase.</td>
<td>boat acceleration</td>
</tr>
<tr>
<td>Pitch Min, Pitch Max, Pitch Range</td>
<td>Minimum, maximum and range of boat pitch angle (up/down movement of bow ball) during one stroke</td>
<td>boat acceleration and gyroscope</td>
</tr>
<tr>
<td>Roll Drive Min, Roll Drive Max, Roll Drive Range, Roll Recov Min, Roll Recov Max</td>
<td>Minimum, maximum and range of boat roll angle (boat tipping to left or right) during drive and recovery phase The same features are extracted for the boat yaw angle (making a turn to bow or stroke</td>
<td>boat acceleration and gyroscope</td>
</tr>
</tbody>
</table>
Table 21: Descriptions of boat-specific features. The column “Sensors” mentions one possible set of sensors that can deliver the necessary raw data to calculate the appropriate feature.

<table>
<thead>
<tr>
<th>Names of features</th>
<th>Description</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>t Drive</td>
<td>Duration (in seconds) of drive phase, recovery phase and total stroke. From that the ratio (in percent) between drive and total stroke duration is also calculated.</td>
<td>Angle sensor at gate</td>
</tr>
<tr>
<td>t Recovery</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t Stroke</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drive:Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ang Catch</td>
<td>Absolute angle of oar relative to the boat at the beginning and end of the drive phase (catch and finish position).</td>
<td>Angle Sensor at gate</td>
</tr>
<tr>
<td>Ang Finish</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ang Stroke Length</td>
<td>Swept oar angle during the drive phase. The angle value (Ang Stroke Length) is also converted to meters (Handle Dist).</td>
<td>Angle sensor at gate</td>
</tr>
<tr>
<td>Handle Dist</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F Max Gate</td>
<td>Force (propulsive direction) at gate. The same two features are extracted for the force at the oar handle.</td>
<td>Force sensor at gate</td>
</tr>
<tr>
<td>F Mean Gate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RFD Ave</td>
<td>Rate of Force Development (average and peak value): Slope of the force curve at the beginning of the stroke.</td>
<td>Angle and force sensor at gate</td>
</tr>
<tr>
<td>RFD Peak</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t Max Force</td>
<td>Time interval from the beginning of the stroke until the maximum oar force is attained.</td>
<td>Angle and force sensor at gate</td>
</tr>
<tr>
<td>Handle Vel Drive Ave</td>
<td>Average and maximal handle velocity during the drive phase.</td>
<td>Angle sensor at gate</td>
</tr>
<tr>
<td>Handle Vel Drive Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Handle Vel Recov Ave</td>
<td>Average handle velocity during the recovery phase.</td>
<td>Angle sensor at gate</td>
</tr>
<tr>
<td>Ang Catch Slip</td>
<td>Both slip values are measures of the rower’s inefficiency at the beginning (catch) and the</td>
<td>Angle and force sensor</td>
</tr>
<tr>
<td>Ang Finish Slip</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Identifying Unique Fingerprints for Rowers and Correlations with Boat Speed

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ang Effective Stk</td>
<td>End (finish) of the stroke respectively. Ang Catch Slip is the catch oar angle (Ang Catch) minus the oar angle when the gate force reaches threshold value (50N) at the beginning of the drive phase. Ang Finish Slip is the finish oar angle (Ang Finish) minus the oar angle when the gate force reaches threshold (10N) approaching the end of the stroke. The total stroke length (Ang Stroke Length) minus both slip values results in the effective stroke length (Ang Effective Stk).</td>
<td>at gate</td>
</tr>
<tr>
<td>Ang Max Force</td>
<td>Oar angle during drive phase at which the maximum oar force is applied.</td>
<td>Angle and force sensor at gate</td>
</tr>
<tr>
<td>Ang Recov Decel Point</td>
<td>Oar angle during recovery phase when boat starts to decelerate.</td>
<td>Angle and force sensor at gate, boat acceleration</td>
</tr>
<tr>
<td>Ang Drive Accel Point</td>
<td>Oar angle during drive phase at which the boat accelerates the most.</td>
<td>Angle and force sensor at gate, boat acceleration</td>
</tr>
<tr>
<td>Power Handle Ave Work Handle</td>
<td>Average power (propulsive direction) applied by the rower to the oar handle during one stroke. The stroke duration and work is calculated with this value.</td>
<td>Angle and force sensor at gate</td>
</tr>
<tr>
<td>Power Drive Ave</td>
<td>Average power (propulsive direction) applied by the rower to the oar handle during drive phase.</td>
<td>Angle and force sensor at gate</td>
</tr>
<tr>
<td>Power Handle Tot</td>
<td>Average power (propulsive and transversal direction) applied by the rower to the oar handle during one stroke.</td>
<td>Angle and force sensor at gate</td>
</tr>
</tbody>
</table>
Table 22: Descriptions of oar-specific features. These features are individual for each rower. The column “Sensors” mentions one possible set of sensors that can deliver the necessary raw data to calculate the appropriate feature.
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[1] **BMA180 acceleration sensor, Technical Specifications, Bosch Sensortec GmbH, Gerhard-Kindler-Straße, 72770 Reutlingen, Germany.**  

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Glossary

2x    Double scull, rowing boat with two rowers with two oars each
2-    Pair without cox, rowing boat with two rowers with one oar each
2+    Pair with cox, like 2-, but additional person for steering in boat
3D    Three-dimensional
AIS   Australian Institute of Sport
ANOVA Analysis of Variance
ANT   Wireless low power communication protocol
API   Application Programming Interface
BT    Bluetooth
CAVE  Cave Automated Virtual Environment
CRN   Context Recognition Network, Toolbox for data recording and annotating [23]
CV    Cross validation
ETHOS ETH Orientation Sensor
FISA  Fédération Internationale des Sociétés d’Aviron, Weltruderverband
GPS   Global Positioning System
### Glossary

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GUI</strong></td>
<td>Graphical User Interface</td>
</tr>
<tr>
<td><strong>HCI</strong></td>
<td>Human-Computer Interface</td>
</tr>
<tr>
<td><strong>HD</strong></td>
<td>High Definition, high resolution video standard</td>
</tr>
<tr>
<td><strong>ID</strong></td>
<td>Identifier</td>
</tr>
<tr>
<td><strong>IMU</strong></td>
<td>Inertial Measurement Unit</td>
</tr>
<tr>
<td><strong>kNN</strong></td>
<td>k Nearest Neighbors; a classifier</td>
</tr>
<tr>
<td><strong>MEMS</strong></td>
<td>Microelectromechanical systems, mechanical sensors integrated into a chip</td>
</tr>
<tr>
<td><strong>NK</strong></td>
<td>NielsenKellermann, company which manufactures rowing accessories</td>
</tr>
<tr>
<td><strong>PCA</strong></td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td><strong>RBAN</strong></td>
<td>Rowing Boat Area Network, instrumented boat [102]</td>
</tr>
<tr>
<td><strong>RF</strong></td>
<td>Random Forest; a classifier</td>
</tr>
<tr>
<td><strong>RMSE</strong></td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>Standard Deviation</td>
</tr>
<tr>
<td><strong>SPM</strong></td>
<td>Strokes per minute, measurement unit for frequency of rowing strokes</td>
</tr>
<tr>
<td><strong>SR</strong></td>
<td>Stroke rate, rowing frequency, usually measured in strokes per minute</td>
</tr>
<tr>
<td><strong>SVM</strong></td>
<td>Support Vector Machine; a classifier</td>
</tr>
<tr>
<td><strong>U23</strong></td>
<td>Under 23 years, age class in rowing</td>
</tr>
</tbody>
</table>