Gait and Balance Assessments in Patients and Weightlifting Athletes Using Inertial and Pressure Sensors

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Acknowledgements

To my parents.
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Abstract

Movement analyses focusing on the walking frame are used in multiple disciplines. However, the existing approaches differ in terms of complexity and significance. There are various methods and sensor systems that sample and analyze human motion. There are clinical methods that base on questionnaires, others require expert knowledge, or use technology to assess the movements of subjects. In sports, expert knowledge and technology are used to assess movements of athletes. The approaches differ significantly in terms of overhead, objectivity and validity.

In this thesis, we address the complementary properties of existing methods and systems. It was our goal to create an autonomous (wearable) multi-modal sensor system. We required the system to be able to detect different static postures: to sit, to stand to lie etc. The system further should be able to distinguish between dynamic situation such as to walk, to run, climb stairs etc. We decided to combine an inertial measurement unit with a high-resolution plantar-pressure sensor to be controlled by a smart phone. Temporal properties of gait and spatial dynamics can be assessed with the IMU. Estimations of dynamic postural configurations and discrimination between multiple static states can be performed with the pressure sensor. The use of a smart phone and its display capabilities allow the creation of a feedback loop that is important for training (physio therapy or athletics).

In the first part of this work, we introduce the physical properties and possibilities of our sensor system. Also, we elaborate on algorithms implemented in firmware and software.

In a medical context, we address gait analyses and assessments of balance. We show that a single device suffices to answer specific questions of clinical relevance by analyzing the step-frequency variability of subjects during dual-task exposure. We use both modalities of our system to show that functional gait analyses (FGA) can be performed to some extent automatically. Further, we focus on balance assessments and show that the system can be used in assessments of patients with benign paroxysmal positional vertigo (BPPV).

In weightlifting, the temporal synchronicity between various muscular groups is important for a successful execution of various exer-
exercises. We analyzed the accuracy in movement during a complex barbell movement with the IMU part of our sensor system. Further, we show that stretching exercises have an impact on weightlifting athletes. We analyzed characteristics of the center-of-pressure (COP) during various weightlifting exercises.
Zusammenfassung


Im ersten Teil dieser Arbeit erklären wir die physikalischen Eigenschaften und Möglichkeiten unseres Sensorsystems sowie algorithmische Details der Firmware und anderer Software-Komponenten.

Im medizinischen Kontext setzen wir uns mit Gang-Analysen (gait analysis) und Analysen des Gleichgewichts (balance) auseinander. Wir zeigen, dass eine IMU-Sensoreinheit reicht, um klinisch relevante Fragen bezüglich der Zusammenhänge zwischen Kognition und posturaler Stabilität zu beantworten. Dazu analysierten wir die

In this chapter, we provide an introduction to this thesis. We present the current state-of-the-art in technology and common practices in medicine, rehabilitation and athletics. We motivate the creation of our sensor system and give an overview on its potentials and application areas.
1.1 Motion Analysis

Measuring the performance and capabilities of the human body has been of interest to science for multiple centuries. As recently as 30 years ago, tools were simple: measurements of time, distance, force or movement accuracy were done without complex technologies. In recent years, with the rise of integrated circuits and MEMS technology, measuring properties of body motion became possible that were not feasible earlier. The sensor systems became smaller, more complex, and more versatile. Embedded sensors that sample acceleration, rotation rates, magnetic field, temperature, light and sensors to measure force applied to a surface became small (typical packaging sizes of inertial sensors are in the order of $2 \times 2 \text{mm}^2$). Further, the cost of these sensors decreased significantly during the last years [1].

The present availability of these technologies has opened doors to complex analysis systems and novel analysis methods. Step counters are implemented in fitness trackers and integrated in shoes [2], in sports watches ([3, 4, 5]), in activity-monitoring wrist bands [6], by applications installed on smart phones ([7]), and also in smart watches ([8]). The capabilities of wearable sensor devices continuously increased. Many include inertial measurement units (IMU) that analyze motion paths of a wearer’s body.

Concurrent to the size reduction of the sensor devices, the algorithms to process their data became more complex. In IMUs, due to sensor noise and other sources of data disturbances, mathematical filters, e.g. Kalman filter [9], complementary filter [10], etc., are needed to create a stable reconstruction of the devices’ orientation. With sensor-device orientation, other systems could track subjects indoors solely relying on data from feet-mounted IMUs [11].

There are other methods to measure full-body movements. Optical motion tracking systems, e.g. Vicon [12] track positions of markers attached to a subject’s body. In combination with plantar pressure-sensitive carpets [13] or pressure-sensitive treadmills [14], optical motion capture systems are used for motion analysis (especially gait) in medicine, but also in athletics. Optical systems allow a detailed reconstruction (typical accuracy of Vicon $60 \mu \text{m}$, [15]) of a subject’s dynamic posture and a pressure sensitive carpet or treadmill allows to reconstruct bio-mechanical details during stance phases.

As the availability and potential of sensor systems have increased in the last years, the combination of multiple sensor modalities con-
stantly created novel applications.

The aim of this thesis was to combine two technologies into a single sensor system. **We believe that the combination of an IMU** with plantar pressure sensors into a wearable and unobtrusive sensor system will open novel possibilities to human motion assessments. In medicine and rehabilitation, we focused on assessments of gait characteristics and balance. In sports, e.g. weightlifting, we were interested in synchronization of different limbs during exercises and in effects of warm-up routines on the balance of weightlifters.

### 1.2 State of the Art

In this section, we provide an overview on state-of-the-art of methods, tools and technologies for assessments of human motion in medical contexts and in athletic contexts.

#### 1.2.1 Traditional Movement Assessments

Movement analysis is the foundation to many medical diagnoses or to therapeutic interventions like physiotherapy. There exists a variety of different movement or mobility indices that assess the quality of movement (most often gait) or other physical performance. The online resource Assessment-Info (GER) lists more than 50 assessments tailored to physical-ability assessments in a clinical context. Earlier studies showed that the risk-of-fall can be estimated from gait parameters [16]. Therefore, balance and gait parameters are assessed in the majority of the indices we studied.

Assessments of movement and mobility can be split into three classes. In the first class, there are questionnaires that are filled in by the subjects. These assessments are tailored to a specific movement area and are designed to find indications of a medical condition. They contain multiple questions (so-called items) that ask for a score within a provided range. The mathematical sum of all answers typically determines the final score of that particular assessment. The Performance Assessment and Capacity Testing (PACT [17]), e.g., comprises 50 items and is designed for people with physical disabilities. The items address multiple activities of daily living (ADL) and other work-relevant activities: a subject can categorize them as "possible to
perform" (score: 1), "only with restrictions" (scores: 2,3,4), and "impossible" (score: 5).

The second class of movement assessments are observation-based: a subject performs a physical task and is watched and scored by an expert. Similar to questionnaires, the final score of the test is the sum of scores for all tasks. An expert needs training and experience to create consistent scores. The Physical Performance Test (PPT [18]), e.g., can be applied to an elderly population and evaluates the ability to perform and time-to-completion of various ADL items, e.g., rise from chair, use a spoon etc. The Barthel Index, BI, [19] is similar: it focuses on people with disabilities or in medical care. In this assessment, ADL are evaluated and rated using 10 items. Due to its simple design and good statistical reliability, the Romberg Test [20] is often used in assessments. Romberg's test assesses the balance performance of subjects. In the original formulation, subjects were asked to stand in an upright posture with their feet together and hands touching their chest for, e.g., 20 seconds. The subjects are asked to close their eyes and an expert watches their postural stability. The Romberg test evaluates noticeable if a subject loses balance and needs to take a step. However, there are occasions where a subject does not need to take a step, yet is still unbalanced [21]. A medical expert might still rate the result as noticeable, even though no step was performed, because a patient's sway was of a too large amplitude. The Romberg's test also requires experience and training to rate a balance-performance consistently, therefore this test can also be assigned to the third class (see below).

In the third class, movement assessments lack a subjective interpretation. These assessments are designed to objectively evaluate the performance of a subject. The "Bewegungsfunktionstest" (BFT) is a clinical test sensitive to reductions of range-of-motion (ROM [22]). The BFT assesses the ROM of multiple joints of a subject's upper and lower-body. Further, it evaluates balance and time requirements for walking tasks. 24 items are tested resulting in a maximal score of 100, which approximates the percentage of reduction in movement ability. The timed up-and-go test, TUG [23] is a standard test. In this assessment, a subject is asked to sit in a chair. The required time to stand up, walk, 3 meters, turn 180 degrees, walk back and take a seat again is measured. TUG has been shown to correlate very well with other established tests assessing mobility, balance and risk of fall [24] (see fig. 1.1).
1.2. State of the Art

Figure 1.1: Timed-up-and-go (TUG): the subject starts in a seated position. The required time to stand up, walk 3 meters, turn around and sit back down is measured.

1.2.2 Technologies for Movement Assessments

Commercially available plantar-pressure systems by TekScan comprise a pressure-sensitive plastic foil [25]. These systems contain sensor arrays in the shape of a shoe insole that can be customized to fit in shoes of arbitrary sizes. The sensor array is sampled at 100Hz and the data are transferred over a cable to an aggregation device an athlete usually wears around the hip. There are also wireless models that transfer data in real-time to a computer. In the system by Tekscan 1260 pressure values are read with every sample at 100Hz.

Inertial measurement units (IMU) attached to the feet, shin, thighs etc. allow a detailed assessment of acceleration and rotation affecting a subject’s limbs while moving. Given a set of accurate sensor devices, velocity as well as motion paths can be extracted [26]. The sensor data or position estimates are forwarded to a mathematical model of, e.g., a subject’s lower body parts. With the inclusion of bio-mechanical restrictions, e.g., maximal joint angles, a full-body motion reconstruction algorithm can calculate an estimate of the body posture for any given moment in time, e.g. [27]. Commercial systems are available from, e.g., XSens, Shimmer.

Optical motion capture systems (OMCS) are also used for gait analyses [28]. Step detection is more complicated compared to IMU-based systems. In OMCS, cameras are rigidly attached to some infrastructural surrounding. Their positions and view-ports need to be known exactly. Also, optical parameters (focal length, distortion, etc.) are calibrated by the manufacturer. Typically, an infrared light source illuminates the scene and the cameras are sensitive in this electro-
magnetic spectrum. Optical markers are attached to a subject prior to any recording. These markers reflect the infrared light omnidirectionally and thus are well visible by the cameras. An OMCS typically consists of 15 or more cameras [12].

Balance assessments are more complex than just step detection. As we have shown above in subsection 1.2.1, balance is an important feature for various movement assessments. In robotics, the state of balance can be assessed reliably, since the physical properties of the device (i.e. robot) are well defined. The mass, position and orientation of every moveable part is known at all times, thus the COM can be calculated at any given point in time. Estimating the COM for humans is difficult. Body parameters are individual, complex to assess, and might change over time. The exact distribution of mass can only be known up to some approximation [29]. IMU-based systems combined with OMCS can also be used for COM estimation, but to achieve accurate reconstruction results, a subject's body needs to be gauged. There exist algorithms that estimate the mass of a subject's body given a set of images with an average accuracy of 4.3% of body mass [30]. The distribution of body mass can be estimated, a body model can be parametrized, and the center of mass can be estimated from a set of images [31]. Thus, IMU systems or OMCS can be used to estimate static and dynamic balance.

A different approach to gait analyses and eventually balance assessments are systems that measure reaction force between feet and ground, i.e. plantar-pressure sensing systems. In 2008, a wearable pressure-sensing insole, combined with an IMU called GaitShoe, was presented by Morris Bamberg et al. [32]. Their system was comprised of four pressure sensitive sensors and an IMU component. The authors successfully used the system in gait analyses and demonstrated a high accuracy in gait-event detection like heel-strike or toe-off events in a comparison to state-of-the-art. The authors also evaluated foot-angles during stand and swing phases. In 2012, Nike presented their new Nike Hiperdunk+ technology targeting basketball players [33]. Their system combined four pressure sensors with an IMU module. The system was integrated in selected shoe models. Sensory data was integrated into the NIKE+ data framework, similar to the Fuelband-technology [2]. The system captured acceleration-based motion data and estimated performance parameters like jumping height, quickness, hustle, etc. In 2011, the Planipes [34] system was presented by Pfaffen et al. The system contains 16 pressure sensors that are
1.2. State of the Art

Figure 1.2: Ambiguity of COP especially in dynamic situation. The subject on the left increased the load on his toes, the right subject reaches out with his hand. The COP is equal in this illustration.

sampled at high speeds (up to $100 \text{Hz}$). The sensor sole connects via Bluetooth to a smart phone which is responsible for data analysis and display.

In medical therapy or in diagnosis and assessments of patients, force-sensitive systems are used to assess balance parameters in dynamic and static postures. State-of-the-art systems are pressure-sensitive carpets, e.g., GaitRite \cite{35}, Kistler force plates \cite{36} or treadmills augmented with force-sensitive surfaces, e.g. Zebris \cite{14}. While a person is walking, these systems track the COP and analyze its motion patterns. Abnormal patterns could indicate potential gait problems \cite{37,38}. Assessments of walking subjects’ balance performances only using force sensors are difficult, because limb positions and body posture are unknown. Force sensors measure the reaction force between feet and ground; thus, sensory data of a subject reaching with one arm to the side (e.g. while walking) creates a similar effect of the center-of-mass (COM) as when she initiates e.g. a small hip movement (see fig. 1.2).

However, it has been shown that ground-reaction forces (GRF) are a valid proxy for the balance while standing. GRF can therefore be used for balance estimation \cite{37}. Analyzing the trajectory of the center-of-pressure, the balance performance of a subject can be approximated \cite{37,39}. The COP is the point on a (virtual) force plate where the torque vector acting on the plate has its origin \cite{40}. To assess the balance using GRF, the motion of the COP can be modeled as a randomly moving particle, i.e. a Brownian particle. So-called stabilograms are used to visualize the model; the model parameters correlate with the randomness of the motion. It has been shown in prior
art that this randomness correlates with bipedal stability and therefore with the risk of fall \cite{21}.

### 1.2.3 Medical Applications for Motion Analysis Systems

In recent years, the correlations between features of gait and risk-of-fall (especially in an elderly population) were investigated. Initially by visual inspection, then by video analysis, researchers found that step-frequency variations are valid features for dynamic postural stability estimations \cite{16,41}. By analyzing patients’ gait, an understanding could be established regarding possible causes or an increased risk of fall (RoF) \cite{16,42}.

Neuropsychologists hypothesized that, with age, cognitive resources become scarce to an extent of where patients have difficulties executing multiple tasks simultaneously. Walking and simultaneously speaking (e.g.) becomes mentally challenging. It has been shown that improvements in gait performance are achieved by a longer-term training process where elderly people are trained physically and mentally \cite{41}.

In patients suffering from Parkinson’s disease (PD), the goal is to reduce the risk of fall and to reduce occurrences of freezing of gait (FoG). FoG forces patients to freeze in an arbitrary position, often while they try to turn or while they are entering a passage \cite{43}. During these episodes, involuntary leg movement, like shaking, can occur and continue for multiple minutes. Recently, it could be shown that presenting visual or auditory cues to PD patients can reduce the duration of FoG episodes \cite{44}. A wearable motion-analysis system analyzed the energy of the Fast Fourier Transform (FFT) on IMU data of patients’ movements. FoG episodes created a characteristic energy signature in a specific frequency band (3 – 8Hz). Machine learning algorithms were trained to learn the characteristics of FoG episodes. If an episode of FoG was detected, auditory cues, e.g., a regular rhythm were presented to the patient through earphones. Patients focused on this pattern and were able to continue their walking.

Wearable motion sensors can be used to reduce the number of required meetings between patients and medical experts. Tailored sensor systems can log patients’ activity or track and assess the efficacy of an intervention (e.g. medication or physiotherapy exercises). In a setting with chronic pain patients, a smart phone was used to assess the efficacy of pain medication and treatment \cite{45}. The authors of the
study hypothesized that patients alter their activity patterns if pain levels were reduced. The system recorded barometer data, accelerometer data and GPS data for more than 26 days. Over the period of the study, the patients reported a 40% decrease in subjective pain levels. The authors found a 10% increase in measured physical activity levels in the same time period.

In a study [46], Stohrmann et al. used a wearable system comprised of 15 pressure-sensitive elements and an IMU to assess cerebral palsy (CP) patients in a home setting. The system stored data at 64Hz. 15 children suffering from CP wore the shoes while COP approximations were estimated and logged continuously. An expert assessed the severity of gait impairment. The authors calculated COP trajectories for all gait cycles with a technique called "Active Shape Model". A support Vector Machine (SVM) learned the classes from the experts’ labels using the model parameters for each active shape model. IMU data was not evaluated. The authors achieved an average classification accuracy of 90% at classifying clinical scores of gait-variation severity.

1.2.4 Movement Analysis in Sports

Athletes aim constantly at improving their performance by optimization of movement. With IMU and OMCS, bio-mechanical experts analyze sport-specific movements and compile the findings into coaching feedback for the athletes.

For example, a reduction of energy expenditure is important for long-distance runners (at least up to marathon distances) [47]. Balancing muscle recruitment is important for multi-discipline sports (e.g. triathlon) [48]. Weightlifters aim at achieving bio-mechanical optimal postures for maximum power generation [49] [50]. Body-environment interaction are optimized for reduced physical resistance (e.g. swimming or cycling). Coaches of various athletic disciplines record athletes’ performances in team sports, e.g. field hockey [51]. Analysis software helps in tracking motion paths of individual limbs or larger body parts in skill assessments [52]. There are video-based systems that calculate the power generated by weightlifting athletes [53].

In running sports, foot trajectories are analyzed with high-speed video footage. Leg positions and joint angles at different stages of a gait cycle can be calculated [54]. In a study, motion-analysis systems prevent runners from running in a sub-optimal posture that eventually
would lead to injuries [55]. The upper arm was identified as a suitable position for a single-IMU sensor system. The authors implemented an application to detect excess torso-rotation while running on a smart phone. The system was attached to the upper arm of 20 runners. The authors evaluated the acceptance of the system and the performance of the algorithms. The authors showed that the participants improved their running technique significantly in respect to upper-body rotation.

Activity trackers like step counters or GPS loggers are commonly used by recreational athletes. In a collaboration, Nike and Apple created a sensor device to be integrated in running shoes (see [2]). Systems like FitBit[6], Polar [4], Garmin vivofit [3] provide the user with more detailed data. They classify the step frequency within a specific time period. These systems are capable of discriminating running from walking and they are sometimes (FitBit One [6], Garmin Tactix [56]) even able to detect vertical ascent or descent using a built-in barometer.

1.3 Benefits of a Multi-Modal Sensor System

In the prior sections we stressed several findings: in medical and athletic applications, state-of-the-art of movement assessments are susceptible to subjective bias (by the expert). Autonomous systems, e.g., step counters or activity monitors, are limited in expressiveness. Finally: comprehensive, full-body assessment frameworks often require an expensive infrastructure effort and they are time-demanding because of setup, acquisition and evaluation.

Prior art has shown that acquiring gait without influencing the subject is difficult. For an analysis of gait features it is favorable to have as little external disturbances (to the subject) as possible. Otherwise, relevant (medically or in sports) features might be disturbed. Subjects alter gait parameters if walking on a treadmill [57]. Even an expert walking with the subjects can influence their speed or other parameters. Most systems require the subjects to walk in confined spaces, usually of limited length/size, e.g., inside a frame for Optical Motion Capture or on pressure sensitive carpets, thus potentially influencing their motion patterns.

To reduce bias through wearing, but also to increase compliance of the users, a sensor system for human motion analysis should be invisible and unnoticeable, i.e. unobtrusive to the wearer. However, if
possible, unobtrusive systems should not require a subject to use or wear an additional item. Prior studies showed that even with high initial acceptance, subjects are more likely to stop using a (sensor) system if there are additional actions required to use it. Attaching a sensor device every morning to a leg was unacceptable for the majority of the subjects in [58] [59].

An unobtrusive sensor system for longer-term continuous use should be integrated into items of everyday use. Current development in commercial products and research reflect this conclusion. Activity-tracker wristbands are intended to remain on a user’s wrist without interruptions between charging cycles. Additional functionalities like a vibrating alarm-clock are an incentive to the user and motivate continuous wearing. Some activity-logging wrist bands feature displays to provide feedback to the users regarding distance walked, calories burnt, heart rate, sleep patterns etc (e.g. FitBit, Polar, Garmin, etc.). In sports, it seems to be more accepted to wear a dedicated item just for a specific activity. The abundance of GPS logger, heart rate monitors etc. indicate that fact. However, also in sports, a long and complicated setup seems prohibitive: sensors should be easy to activate and use.

In a lifestyle context (i.e. non-medical and non-athletic), recent commercial developments promote smart watches as unobtrusive activity monitoring systems with advanced functionalities. Common to all proposed systems are an interactive display and advanced notification functionalities. These devices are tightly coupled to users’ virtual identities. Some products feature capabilities to autonomously access the Internet, others require a smart phone as a gateway (Samsung Galaxy Gear, Pebble Smart watch, etc.). The most popular systems contain an IMU plus additional sensors, e.g., temperature, air pressure light intensity etc. The products differ, however, in the accessibility of the data. Some systems provide application programming interfaces (API) for developers that allow full access to raw data. Others only provide access to aggregated or filtered data. Smart phones are often carried in pockets, in hand, in belt pockets or in other locations [60] [61], e.g. on a working table. Smart phones therefore are excellent for outdoor location tracking and, to some extent, movement tracking [55]. However, they are limited in their capabilities to comprehensive, uninterrupted movement tracking in medical and athletic context.
1.3.1 Proposed System

Our aim was to create a multi-modal sensor system that is able to assess features of bipedal performance. Partial unobtrusiveness was achieved by the integration into shoes: a regular item that is worn by the major part of the western population. However, a miniaturization of the electronics modules would be required to achieve full unobtrusiveness. In the previous sections, we presented the state-of-the-art in movement analysis. The capacity of estimating the dynamic and static posture was an important requirement to such a system. The timed up-and-go (TUG) scores have been shown to correlate well with the dynamic and static posture stability (i.e. risk of falling). However, also assessments that evaluate balance directly are used in clinical settings, e.g. Romberg's tests [62].

We decided to combine two modalities: a plantar pressure-sensing module and an IMU. It has been shown in prior research that IMU data provides valuable feedback for a movement analysis system (e.g., activity, steps, 3D path etc.) [27, 63, 64]. Measuring reaction forces between feet and ground allows to discriminate between sitting and standing with a single sensor module. A high-resolution pressure map allows to estimate center-of-pressure dynamics and possibly biomechanical imbalances while walking or standing. The integration of a smart phone created unobtrusive possibilities for high-level calculations, user-feedback and context recognition.

We built a sensor system that combines a flexible matrix of pressure sensitive elements with an inertial measurement component which samples acceleration, rotation rates and magnetic field values in three dimensions.

We call our system PIMU for Pressure-sensitive IMU (see fig. 1.3). We present the details of PIMU in chapter 3. In chapter 4, we elaborate on aspects of the firmware that enabled data storage at 100Hz. Fig. 1.4 provides a graphical overview on the system.

1.3.2 Applications

We deployed and tested our system in three different domains: gait analysis, balance assessments (bipedal performance) and athletics (weightlifting). In gait analysis (see chapter 5), we used an IMU component and assessed the impact of dual-task exercises in elderly people. We were interested in changes of step frequency. In a follow-
1.3. Benefits of a Multi-Modal Sensor System

Figure 1.3: The PIMU system. The plastic housing holds the IMU module and the pressure-sensing module. The pressure-foil in this image is unaltered. The beige-colored lines are connections between the ADC and the pressure-sensing elements.

Figure 1.4: The components of PIMU. The pressure-module samples the FSR elements with 32 ADCs and communicates via I²C to the IMU. On the IMU, data are stored on the SD card; wireless communication is also handled on the IMU module.
up study, we used PIMU to assess COP features and gait-frequency changes in patients suffering from symptoms affecting their ability to balance their posture (chapter 6). We measured the subjects during functional gait assessments (FGA performed by physio therapists) that were conducted to assess requirements for further physiotherapy.

In a recent study, we used PIMU to assess balance performances in patients suffering from BPPV (Benign Paroxysmal Positional Vertigo). We compared the postural stability of patients to the postural stability of healthy subjects before and after therapy (see chapter 7).

In an athletic environment, we deployed multiple sensor devices and used the IMU component. As the sensor data was synchronized between multiple sensor nodes, we were able to analyze multi-joint weightlifting movements (chapter 8). We showed that by looking at the movement-synchronization accuracy in multiple athletes, an automatic distinction between beginners and advanced athletes is feasible. In another study, we used the pressure component of the sensor system to analyze the effects of a stretching routine and of a warm-up routine in athletes (chapter 9). We could show that a tailored stretching is similarly effective on mobility and flexibility than a general warm-up routine.

1.4 Objectives of this Thesis

The contents of this thesis are structured into four parts. We show in fig. 1.5 an illustration of the structure. In the first part, we present the PIMU sensor system in detail (chapter 3, chapter 4). Then, we show how this multi-modal sensor system can be used to augment and support state-of-the-art approaches in gait analysis (chapter 5, chapter 6). Then, we show how the system can be used to assess the balance of healthy subjects and patients (chapter 7). Finally, we show applications of this unobtrusive sensor system in an athletic context (chapter 8, chapter 9).
### 1.4. Objectives of this Thesis

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**Figure 1.5:** The publications contributing to this thesis. The positions of the bars reflect the approximated contributions to a specific field. For example, Chapter 3 is about the pressure sensor and the IMU in approximately equal parts.

Specifically, the following topics will be investigated:

1. **Combining two sensor modalities into a comprehensive system**
   In Chapter 3, the hardware of PIMU is explained in detail. We present the capabilities of the firmware and provide an evaluation on classification accuracy between sitting, standing and walking. In Chapter 4, we provide details on the optimization of the firmware to enable pressure-data acquisition at 100Hz.

2. **Gait timing and COP in medical context**
   We show that the synchronization of the IMU modules allows gait analyses in subjects with gait irregularities (Chapter 5). We further show that PIMU can be used to support or complement assessments in functional gait analyses done by medical experts (Chapter 6).
3. **Balance assessments in patients using COP**
   We demonstrate the applicability and value of the sensor system in medical settings. We show that the pressure module can be used to evaluate differences of balance performance in healthy people and in patients suffering from BPPV (chapter 7).

4. **Movement timing and COP in athletic contexts**
   We show that an accuracy of synchronization in the order of $10\mu s$ between multiple modules allows for detailed movement analyses in athletes (chapter 8). We further show that center-of-pressure (COP) analyses in athletes allow to draw conclusions on the efficacy of a warm-up or a stretching routine in athletes (chapter 9).

### 1.5 Thesis Outline

This thesis includes seven publications and it is structured in 9 chapters. Our contributions are divided into four parts as presented in the previous section. In fig. 1.5, the topics are illustrated and the related publications are referenced. Chapter 2 provides a summary of the thesis. Chapter 3 and following present the individual publications.

The following publications are included in this thesis:

- **Chapter 3**: R. Adelsberger and G. Tröster, *PIMU: A wireless pressure-sensing IMU*, ISSNIP 2013, [65]
- **Chapter 4**: R. Adelsberger and G. Tröster, *Enabling high-speed data acquisition with compressive sampling*, BSN 2014, [66]
- **Chapter 5**: R. Adelsberger and G. Tröster, *One IMU is sufficient: A study evaluating effects of dual-tasks on gait in elderly people*, MobiHealth 2012 [67]
- **Chapter 6**: R. Adelsberger and G. Tröster, *Unobtrusive Assessment of Bipedal Balance Performance*, BodyNets 2013, [68]
• **Chapter 8**: R. Adelsberger and G. Tröster, *Experts lift differently: Classification of weight-lifting athletes*, BSN 2013, [70]


During the PhD studies, we additionally published the following papers, but they were not included in this thesis:


• R. Adelsberger and G. Tröster, *On the benefits of a poly-cultural sensor setup: Controlling embedded sensors with a smart phone*, ERCIM 2013, [74]

• R. Adelsberger, *Capturing Human Motion One Step at a Time*, XRDS Crossroads ACM, [75]

• R. Adelsberger and G. Tröster, *Unobtrusive exercise assessment for weightlifting athletes*, 3D AHM 2014, [76]

• F. Gravenhorst, C. Thiem, B. Tessendorf, R. Adelsberger, B. Arnrich, C. Draper, R. M. Smith and G. Tröster, *SonicSeat: design and evaluation of a seat position tracker based on ultrasonic sound measurements for rowing technique analysis*, JAIHC, [77]

In this chapter, we present the contributions of this thesis. We present the development and evaluation of a novel sensor system and research based on the deployment of that system. We show the system's applicability in athletics and medicine and present the findings of multiple studies. This summary is arranged according to the structure presented in chapter 1. Detailed discussions can be found in the corresponding publication chapters.
Chapter 2: Thesis Summary

2.1 Sensor System Technology

Prior to developing the sensor system, we conducted a review of the state-of-the-art in current practices of functional gait assessments, risk-of-fall estimations, and balance assessments in elderly people and patients with vestibular deficiencies. We identified two main modalities and multiple requirements that needed to be fulfilled by the future system. The need for accurate step detection and gait feature extraction (i.e. timings etc.) motivated the inclusion of an inertial measurement unit, IMU. Balance estimation and estimation of features of gait during the stance phase required a measuring device for plantar pressure. The combination of both sensors (IMU and plantar pressure) enabled the system to automatically distinguish between multiple body postures (sitting, standing, etc.) and dynamic context (walking, climbing stairs, etc.) with a minimal number of devices (i.e. one foot equipped with the system). If two sensors were attached to the feet of a subject, balance assessments were feasible based on the COP of both feet. A wireless connection to a display and computation device, e.g. a smartphone, opened novel possibilities for training-feedback in sports and rehabilitation. A storage unit enabled long-term monitoring of subjects’ performances during activities of daily life.

2.1.1 Combining Pressure and Inertial Data (PIMU)

The combination of multiple sensor modalities enabled autonomous and automatic detection of different body postures with one single device. We proposed the combination of a plantar-pressure sensitive module and an IMU. We called this combination PIMU for pressure-sensitive IMU. A PIMU device can discriminate between the static postures standing, sitting, lying. Body dynamics can also be detected and classified into walking, climbing/descending stairs, running, etc. The discrimination between various static and dynamic postures enables automated assessments like the timed-up-and-go (TUG) test. This test is abundantly applied in patients with balance deficiencies and also in elderly people. TUG scores have shown to be excellent surrogates for the risk-of-fall (RoF) [79]. Especially in an elderly population, estimating the RoF of a subject is crucial as potential injuries resulting from a fall are often severe. The PIMU system can automatically assess TUG score and can therefore be used for an automated estimation of RoF.
Fig. 2.1 illustrates the layout of the PIMU system. The plantar pressure module is connected to a pressure-sensitive polymer foil manufactured by TekScan [25] in the shape of a foot (see fig. 1.3). Through a grid structure, the individual force-sensing resistors (FSR) are connected to a micro-controller unit responsible for analog-to-digital (ADC) conversion of the resistance readings from the sensing elements. If pressure is applied to a FSR element, its resistance is decreased. This decrease of resistance is measured by the ADC. One sensor foil contains 1260 FSR elements. The size of the foil can be adapted by cutting along pre-defined lines for the cost of losing some FSR elements, but otherwise not affecting the performance. The ADC component samples the pressure sensor with 100Hz, thus creating data at approximately 1MBit/s. The inertial-measurement-unit module (IMU) is comprised of a 3D-accelerometer (LIS3LV02DL by STMicroelectronics), a 3D-gyroscope (ITG-3200 by InvenSense) and a 3D-magnetometer (HMC5843 by Honeywell). On the IMU module, a wireless communication IC implements the low-power ANT+ network stack. ANT+ is a proprietary multicast network technology for wireless sensor networks developed by Dynastream Inc. Further, sensory data from the IMU and the pressure module are stored on a SD-card. The two modules (IMU and pressure) are connected via I²C. A Li-Ion battery with a typical capacity of 400mAh provides power to the entire PIMU system for typically (64Hz IMU sampling frequency, 32Hz ANT+ communication frequency) 10 hours; but this depending on sampling frequency and wireless communication settings.
Figure 2.1: A diagram of the PIMU system. On the left side, the pressure-acquisition module is depicted. It is connected via I2C to the IMU module. On the right side, the pressure-acquisition module is depicted. It is connected via I2C to the IMU module.
2.1. Sensor System Technology

A remote device (a smart phone or a computer) communicates wirelessly to the PIMU systems. We implemented functionalities to control and configure individual sensors through a simple graphical user interface (see fig. 2.2). Further, PIMU modules report power levels and other system messages to the remote device.

Figure 2.2: Screen shot of the control application running on a smart phone. In this view, the buttons for the control commands are visible: “Start Sampling”, “Stop Sampling”, etc. The application also supports a video recording functionality: camera data is displayed. The video recording only starts as soon as all registered nodes reported a successful start of acquisition, thus, video data is synchronized to PIMU data.

We assessed various characteristics of the system. For multi-PIMU settings, the synchronization jitter between multiple sensors is on average $10.1 \mu \text{sec}$ which is sufficient for all intended application areas. Inertial data is acquired and stored at a maximal rate of $512 \text{Hz}$. Pressure data is available at $100 \text{Hz}$. We assessed the hardware characteristics of the pressure-sensitive foil. Firstly, the cross-talk between two neighboring FSR was assessed: we measured how much the readings for an idle FSR would change if force was applied to a neighboring FSR. We used materials testing equipment by Zwick/Roell to exert in a controlled way force to a single FSR cell while the pressure system was sampling also the adjacent FSR elements. Cross-talk was present between two adjacent FSR (correlation coefficient of 0.75), but it was negligible for more distant FSR (see fig. 2.3). FSR elements reacted to applied force according to literature and exhibited a dynamic range.
of resistance depending on applied force of
\[
[150\Omega - 5M\Omega] \propto [40N - 0N]. \tag{2.1}
\]

Power consumption of the IMU module was depending on sampling frequency and the usage of the wireless transmission functionality. Power consumption of the pressure module was linearly dependent on the sampling frequency. For gait analyses, the power requirements of PIMU were in the order of 60mA.

![Figure 2.3: Analyzing the cross-talk on a patch of 3×3 FSR elements. The cross talk is significant for two adjacent cells, but it fades off rapidly for more distant sensing elements.](image)

On the pressure module, we implemented algorithms to calculate statistical features and features based on 2D characteristics of pressure data. The features "mean pressure", "maximal pressure patch" and the "principal axis" of the maximal pressure patch were calculated in real time. On the IMU module, using both inertial and pressure data, a classification routine was calibrated to differentiate between standing, sitting and walking using IMU and pressure data. The accuracy of the classifier detected the classes correctly with 99% accuracy.

2.1.2 Real-time Data Reduction to Overcome Bandwidth Limitations

As explained in the previous subsection, PIMU is comprised of two distinct modules, an IMU and a plantar-pressure sensor system that are connected via I²C. At 100Hz sampling rate, the pressure system generates data at approximately 1MBit/s. However, the I²C channel is limited to 400kBit/s. Thus, about 2.5 times more data are generated than could be transferred to the IMU where data is stored. See fig. 2.1 for an overview on the hardware layout.
Current plantar-pressure systems and algorithms (e.g., [80, 81]) require full-resolution data samples that are acquired with at least 100 Hz to calculate statistical features. Therefore, to match the capabilities of existing systems, it was not an option to implement spatial sub-sampling (reducing spatial resolution) or temporal smoothing (reducing temporal resolution) to overcome the bandwidth limitations. Common compression algorithms are designed to feature a short deflation time, but require more complex computations during compression ([82] [83] [84]). As PIMU does not use a processor with sufficient computational power to deal with that class of compression algorithms, our requirements were opposite. We needed a solution with feasible computational complexity for PIMU. Because for logging or monitoring applications no real-time behavior of the system was intended (i.e. the system was not expected to react upon an event), data-reconstruction time was not critical.

In compressive sampling (or sensing) (CS) the compression step is of low complexity. Candès et al. [85], defined the compression step as a matrix-vector multiplication of a (sparse) data vector $x \in \mathbb{R}^n$ with a random matrix $A \in \mathbb{R}^{m \times n}$:

$$y = Ax \quad (2.2)$$

Because $A$ is a rectangular matrix with $m \ll n$, it holds that $\dim(y) \ll \dim(x)$. Reconstruction of $x$ is performed using convex optimization which is feasible, because $x$ (the original data) is required to be sparse. To recover the best estimate of $\hat{x} \approx x$, the following convex optimization program needs to be solved (see [85]):

$$\hat{x} = \text{argmin}_{y = Ax} (\|\hat{x}\|_{L^1}) \quad (2.3)$$

The $L^1$-norm is defined as

$$\|x\|_{L^1} = \sum_{i=1}^{n} |x_i|. \quad (2.4)$$

Convex optimization problems generally require significant computational power.

From pressure data acquired in prior tests, we learned that differences between two consecutive pressure sample were small (see fig. 2.4). Thus, to increase sparsity, we designed a differential encoding where we calculated the difference between two following frames
and used these data for further processing. To keep error propagation limited, every $100^{th}$ frame was transmitted to the SD card without differential encoding.
Data pipeline for compression. First, sparsity is increased by calculation of difference frames. The data vector $x$ is compressed by a matrix-vector multiplication with the sensing matrix $A$. The lower-dimensional result, $y$, is finally stored on the SD card.
Chapter 2: Thesis Summary

The data-compression pipeline is visualized in Fig. 2.4. On the pressure module, the differences between consecutive frames are calculated. Data size is reduced by performing the compression step, i.e. a matrix-vector multiplication of the sensing matrix with the data vector. The resulting compressed representation is transferred via I²C to the IMU module where it is stored. Reconstruction of the original data is performed on a regular desktop computer solving equation 2.3 for each frame to be recovered.

We tested our compression/recovery pipeline with stored data from prior acquisitions. The random sampling matrix $A$ is of size $1260 \times 252$. Thus, after $y = Ax$, only $1/5^{th}$ of the original data size ($\text{dim}(x)$) needs to be transmitted. We compared the RMS error between 100 data frames and the respective reconstructions. For every frame, PIMU calculates the center-of-pressure (COP) coordinates. COP calculations are unaffected by noise or data offset (see the formula for COP in [40]). Thus, the RMS error is a sub-optimal measure for the fidelity of a reconstruction. We therefore defined a RMS measure based on COP:

$$E_{real} = \sqrt{\frac{1}{2} \sum_{i=1}^{2} \left( COP_{i}^{\text{orig}} - COP_{i}^{\text{rec}} \right)^2}$$

(2.5)

$COP_{i}^{\text{orig}}$ were COP coordinates of frame $i$ calculated on an unprocessed frame, $COP_{i}^{\text{rec}}$ were COP coordinates calculated on the reconstruction of frame $i$.

We assessed $E_{real}$ on 6000 frames. The RMS error was 0.302 coordinates which is equal to a root-mean squared distance between the estimated $COP_{i}^{\text{orig}}$ and $COP_{i}^{\text{rec}}$ of 1.5mm. This was found to be sufficient for our applications and we implemented the CS pipeline as described on the PIMU system. The data reduction to $1/5^{th}$ is sufficient to allow full-speed pressure-data acquisition at 100Hz.

2.2 Analysis of Gait

Gait plays a crucial role in the quality of life and it is of high importance to patients for re-establishing or maintaining physical independence. In subsection 2.2.7, we present our research on correlations between cognition and gait. We based our study on findings by related work that showed that gait irregularities are linked to increased risk
2.2 Analysis of Gait

Subsection 2.2.2 targets clinical testings and establishes our pressure-sensitive IMU as a complementary possibility to existing state of the art.

2.2.1 Gait Characteristics as an Indicator of Cognitive Load

As the percentage of the elderly population increases in industrialized countries, more effort is invested in research focusing on aged people. Current research is working on a more complete understanding of the effects of aging on gait and its cross-effects with cognition. It has been shown that in an elderly population cognitive tasks can have a significant impact on regularity of gait [86]. Irregular gait was linked to an increased risk of fall [87]. In chapter 5, we present results from a study in elderly patients. We showed that a single sensor unit (one IMU) suffices to perform analyses on gait features. We further showed that there was a measurable effect of dual-task exposure on specific gait features in elderly subjects.

State-of-the-art in neuro psychological gait analyses are walking tasks where subjects are asked to walk along a straight path of typically 10 meters. The subjects are recorded by video and their deviation from a straight path and other irregularities of gait are recorded manually by an experimenter. In our study, we asked the subjects to walk two times a distance of 10 m, i.e. to and from a turning point (see fig. 2.5b). The subjects were equipped with inertial sensor units attached to both shins (right below the knees) and both thighs (see fig. 2.5a). Simultaneously, the study participants were recorded by a video camera for later annotations.

The subjects were recruited from an elderly population, were aged 65 years or older, and did not show significant cognitive signs of aging, i.e. they scored with more than 26 points in the Mini Mental State Evaluation [88]. The subjects were also evaluated with the timed-up-and-go, TUG, test [79] to ensure that no significant deficiencies in mobility were present.
Figure 2.5: Test illustration and sensor placement for the dual-task study.

(a) Four IMU devices attached to the shins and thighs of a subject.
(b) The walking tasks required the subjects to walk along the illustrated path.

Transmit Station

Shin

Thigh

Start
The IMU sensors recorded acceleration and rotation rates at 100Hz.

A total of 48 elderly subjects participated in the study. The study protocol required the participants to perform a walking tasks twice. In a first instance, the subjects were asked to walk with an individual, but fast pace. In the second part, the subjects were required to walk the same path again while performing a mental task: from a random number close to 500, the subjects were asked to consecutively subtract 7 while walking and stating the results.

In a later step, the recorded data were analyzed on a PC. For all analyses we used data from one shin sensor; data from the other sensor devices were redundant, i.e. did not reveal additional information. From the accelerometer signal, a step-detection algorithm extracted the timestamps for all steps. The two steps before, all steps at, and two steps after the turning point were neglected from the data set. On the step duration, we calculated the statistical features mean, variance, and median. We performed repeated two-factor analysis of variance, ANOVA.

The analysis revealed that an increase of cognitive load significantly impacted features of gait, e.g. step duration variability, in the assessed group. In fig. 2.6, the differences of step duration between with and without dual task are visualized in a cumulative probability plot.
Mean step duration increased significantly \( (p < 0.007) \) by a mean value of 34\,ms if subjects were exposed to cognitive load. The standard deviation of step durations also increased statistically significantly by approximately 5\,ms.

The findings were in line with prior studies (e.g. [86]). To the best of our knowledge, for the first time gait assessments could be objectively performed with data from a single small sensor unit. Statistical features of step duration contained sufficient information for the automated distinction between dual task and single tasks. With this study, we further motivated the development of PIMU and showed that a single IMU provides valuable data to clinical gait analyses.

2.2.2 Supporting and Augmenting Functional Gait Assessments with Automatic Tools

There is a range of medical conditions that affect the postural stability of patients, i.e. from neurological problems to post-surgery conditions [89]. Depending on the cause, medication and/or training can improve the balance of a patient. In clinical settings, well-trained experts perform functional gait assessments (FGA) in patients with balance conditions. The experts’ subjective interpretation defines the outcome/score...
of the assessment. Some FGA include feedback from patients - usually questionnaires. According to physiotherapists, technological support is not frequently sought due to space restrictions of the location and time restrictions of the treating expert. We show in chapter 6 that the combination of a pressure insole with an IMU enables automated assessments of static and dynamic postural stability. Static postural stability can be assessed by a stabilogram diffusion analysis (SDA) [21]. In a SDA, the motion of the COP in a static pose is analyzed over multiple time intervals. As we explain in detail in chapter 6, the results of a SDA classify episodes of standing into stable and unstable stance.

We compared the performance of our system, PIMU, to similar systems, e.g. Zebris Rehawalk [14] (see fig. 2.7), in terms of accuracy of estimation of the center of pressure, COP. The system by Zebris is used for gait analyses in the local hospital. This system features a pressure-sensitive surface below the moving surface of a treadmill. Additionally, a safety harness secures users and prevents them from injuries in case of falls.

![Product picture of the Rehawalk system by Zebris. A pressure-sensitive surface below the moving surface registers gait features. A safety garment protects the users in case of falls. (Image ©Zebris, 2014)](image)

To compare the accuracy of our system to Zebris Rehawalk, we acquired data from subjects standing on the Zebris system while wearing PIMU. Amongst other information, statistics of the COP were provided by Zebris. COP values were reported as integer numbers by Zebris.
The comparison between our system and the Zebris system was based on the error between COP coordinates reconstructed by Zebris and coordinates estimated by PIMU. Zebris Rehawalk features a spatial resolution of 160 mm² covering a sensitive area of 112 cm × 49 cm. Zebris did not publish the algorithm to calculate the COP. Each FSR element of PIMU covers 25 mm² and they are arranged in a shoe-shaped area. We recorded a subject standing for 30 seconds on Zebris Rehawalk while concurrently wearing PIMU on both feet. In a first step, we compared the COP coordinates provide by the Zebris system to the coordinates calculated by PIMU.

![Diagram showing COP comparison between Zebris and PIMU](image)

**Figure 2.8:** The COP from the Zebris system (blue, left) was available as integer numbers and differed from PIMU's COP (red, right). Our algorithms on the Zebris data calculated the green (left) COP. The RMS error between the green and the red COP was approximately 1.6 mm.

To remove possible bias induced by Zebris' integer coordinates and by different COP calculation strategies, we applied our algorithms for COP calculation to the data recorded by the Zebris Rehawalk system. The RMS error for the first comparison (black-box vs. PIMU) was approximately 5.3 mm. The second comparison reduced the RMS error to approximately 1.6 mm (see fig. 2.8).

We deployed the validated system in 11 subjects: 6 patients and 5 healthy subjects were recorded by two PIMU systems. The patients
were assessed by a medical expert using an augmented FGA consisting of 12 items. The FGA contained 10 walking-related items, like walking and looking up/down or right/left. Items 11 and 12 required the participants to stand still for 20 seconds with eyes open (item 11) or eyes closed (item 12). To assess static postural stability, our system calculated a SDA [21] on the data from item 11 and 12. To assess dynamic stability, we extracted statistical features of the COP for five dynamic items. We trained a SVM to differentiate between stable and unstable static situations. Ground truth for unstable dynamic situations was provided by the medical expert's rating of the according items. A SVM was trained on COP features (standard deviation, range) and on step-frequency features (standard deviation and mean) to discriminate between episodes of instability in dynamic items. Detection of unstable static situations were detected with 93% accuracy; differentiation between stable and unstable dynamic episodes were detected with 91% accuracy.

2.3 Balance

Quantifying balance is an important task for medical experts. The balance performance of a subject contains information about their neurological and their physiological state. Optical motion capture, e.g. Vicon [12], requires often more than 60 minutes to setup, it is typically performed in a constrained dedicated environment, and requires often long post-processing. Additionally, long-term assessments of performance of patients are favorable to a comprehensive diagnosis. However, monitoring patients’ balance over longer periods of time is still a challenging endeavor in rehabilitation and medicine. In the following subsection, we present a study on balance performance in patients with Benign Paroxysmal Positional Vertigo (BPPV). We show that the PIMU system’s accuracy renders ad-hoc assessments of balance feasible and also enables longer-term monitoring of balance due to its unobtrusiveness and storage capabilities. In the respective chapter [chapter 7], we further present clinical findings on balance performance of patients and healthy subjects before and after therapy.
2.3.1 Assessing Short-Term Effects of Liberation Maneuvers in BPPV patients

BPPV is a common disease of the vestibular system (located in the inner ear): 2.4% of the world’s population is diagnosed once in a lifetime with BPPV [90]. Vertigo is kind of dizziness in which a patient (wrongly) experiences the perception of motion. BPPV is caused by detached calcium carbonate crystals that float freely in the endolymph (the fluid contained in the membranous labyrinth of the inner ear) of the vestibular labyrinth (the various canals, see fig. 2.9).

![Illustration of the inner ear.](image)

Normaly, these crystals are attached to the otolithic membrane where they enable the sensing of linear acceleration including gravity. If free-floating crystals happen to enter one or more of the three semicircular canals, BPPV is caused whenever patients re-orient their heads relative to gravity. Since the specific weight of the crystals exceeds the specific weight of the endolymph, the crystals always sed-
2.3. Balance 37

iment to the lowest point of the affected semicircular canal, thereby causing a temporary deflection of its cupula.

Luckily, the therapy for BPPV is simple, yet effective: liberation maneuvers, where a patient’s head is turned according to a specific protocol, result in a successful treatment for more than 90% of the patients after the first therapy [91]. In prior research, patients reported an increased sensation of unsteadiness after liberation maneuvers [92]. In chapter 7, we present a study where we investigated whether that effect could be quantified.

In the study we investigated the following three questions:

1. **Q1**: if balance performance differs between BPPV patients and healthy subjects;

2. **Q2**: if balance performance is affected by liberation maneuvers in patients; and

3. **Q3**: if liberation maneuvers only affect the balance performance of patients, but not of healthy subjects.

An established assessment for balance performance is Romberg’s test [62]. We based our assessments of balance performance on Romberg’s test: subjects were asked to perform three tasks. First, they needed to stand still with eyes closed and heels together on solid ground for 20 seconds. Secondly, they were asked to perform the same task while standing on a foam mat (see fig. 2.10a).
Thirdly, we asked the subjects to stand in tandem stance (heel of one foot touching the big toe of the other foot) with eyes closed (see fig. 2.10b). During all three tasks, patients and healthy subjects were standing on the plantar pressure sensor of PIMU. All subjects received therapy after the first set of balance-assessment tests. Patients were treated regularly, healthy subjects received one liberation maneuver for the left side and one for the right side. Directly after the therapy, the same three balance-assessment tests were performed and again recorded by PIMU.

We then analyzed the COP statistics for all participants and all tasks. We calculated features of the COP (e.g., mean, standard deviation, etc.) and based our analysis for answering questions Q1, Q2, and Q3 on these numbers.

We assessed 7 patients and 9 healthy subjects. We answered Q1 by showing that balance performances between healthy subjects and patients differed statistically significantly prior to the therapy. One finding was that healthy subjects maintained their COP about 5 mm closer to the heels during the Romberg tests. We also received a statistically significant result in answering Q2: the balance performance in patients was affected by the liberation maneuvers. Patients shifted their mean COP towards the toes in the first two tests on average for about 7.5 mm. The answer to Q3 was clinically surprising as both sub-
ject groups showed a reaction to the liberation maneuvers. Healthy subjects shifted the mean COP coordinates approximately 3mm to the heels. Related research done in prior art hypothesized that there should not be a statistically significant effect of the liberation maneuvers in healthy subjects.

2.4 Movement Analysis in Weightlifting Athletes

In weightlifting, the goal is to lift as much weight as possible adhering to standards of an exercise, e.g. "Snatch", "Overhead Squat", "Back Squat", "Clean & Jerk", etc. The exercises require muscular strength as well as joint mobility for successful executions.

Professional athletes are assessed in training on a regular basis with optical motion capture or other technology, but these solutions have drawbacks regarding setup time and infrastructure dependencies. Results from optical motion capture systems require the interpretation of data by an expert. Video capturing ([53]) is also used by athletes to analyze the execution of the exercises. Sports coaches, on the other hand, provide verbal, visual or tactile corrections to an athlete and are not always available to recreational athletes.

In chapter 8, we investigated the feasibility of our sensor system to analyze complex barbell exercises regarding the synchronization of multiple body parts. We showed that the system could provide feedback to athletes allowing them to improve on their technique while practicing. In chapter 9, we showed that our system can be used to detect physiological changes in flexibility induced by warm-up or stretching routines. This could help in future applications to detect suboptimal preparation to an exercise or it could predict injuries due to a lack of proper technique.

2.4.1 Performance and Proficiency Analysis in Weightlifting using Synchronized IMU sensors

The synchronization of multiple body parts is required in weightlifting exercises. To propel a barbell from ground to shoulder height or even to an overhead position, a synchronized sequence of movements of legs, hip and upper-body parts is required. A main principle of barbell movements is to apply consecutive phases of acceleration to the barbell using different body parts. In chapter 8 we analyzed a squat-press
exercise, referred to as "Thruster", in a functional-fitness context. For a successful Thruster, an athlete starts with a barbell in the front-rack position, squats and then accelerates the weight in a fluent motion overhead (see fig. 2.11).

![Figure 2.11](image)

**Figure 2.11:** Start and end position for the Thruster exercise. The barbell starts in the front-rack position and is pressed overhead in a fluent motion while the athlete stands up.

The momentum created with the legs should support the final stage of the exercise where the weight has to be pressed overhead. Crucial to the exercise is the transition between leg and arm. That is the moment where the main upward thrust shifts from being driven by the legs to being driven by the arms. If an athlete fails to push at the optimal moment, they will not be able to exploit their body’s full potential.

We used the [IMU](#) modules of PIMU to analyze the synchronization accuracy of lower-body and upper-body in athletes of various experience levels. We attached three sensor modules to the athletes: on the ankle to detect foot motion, on the hip to track core motion, and on the wrist to track arm and barbell motion (see fig. 2.12). The sensors recorded acceleration and rotation rates at 100Hz.
16 athletes participated in the study; 12 male and 4 female. We asked them about their experience level, ranging from beginner to expert (0-4) and recorded their body height, weight and squat depth. These physiological parameters were used to calculate the physical work and power created by each participant. The athletes were asked to perform two sets of 10 Thrusters at an individually chosen weight and one set of 3 or more Thrusters at a subjectively heavy weight. The first two sets were used to expose differences between novice and experienced athletes. The last set of Thrusters was acquired to detect signs of exhaustion.

An experienced coach watched the participants and classified the individual Thruster-executions into four classes: "poor", "fair", "good", and "perfect".

On a computer, algorithms detected the intervals of Thrusters and extracted the individual Thruster executions. For each Thruster instance, we analyzed the time differences between lower-body and upper-body activation, the lower-/upper-body work ratio and the overall work (see fig. 2.13).

A SVM was trained on 75% of the data and evaluated on the rest. Thrusters were detected with 100% accuracy compared to the manual assignments by the coach. The sensor system analyzed 320 Thrusters \((10 + 10) \times 16\) and could successfully classify them into the four classes.
with more than 93% accuracy overall. Further, in a second classification task, the system successfully analyzed separated beginners form advanced athletes with 94% accuracy.
Figure 2.13: Data from three Thrusters. The curves represent the accelerometer magnitudes of the hip and the wrist IMUs. We analyzed time differences between the curve peaks of the hip (blue arrow) and the arm acceleration (red arrow), the ratio between hip and arm work and overall power.
2.4.2 Assessments of the Effects of Different Preparation Routines in Weightlifting Athletes

Synchronization is a key component of a successful weightlifting exercise. Physical strength, precision of movements and body flexibility are also important factors that impact the performance of athletes. A strength increase in specific muscles can be achieved by resistance training; there are many routines published that gradually increase muscular strength [93]. Flexibility refers to an athlete’s capability of reaching defined start and end positions (postures) during an exercise. A lack of sufficient flexibility forces an athlete to compensate with other joints or entire body parts. For example, in an overhead squat (OHS), a lack of hip mobility often has to be compensated by the shoulder in order for an athlete to maintain a balanced and stable posture (see fig. 2.14).

![Overhead Squat](image)

**Figure 2.14:** Showing the Overhead Squat with sufficient (left) and insufficient (right) mobility. In the insufficient case, the athlete needs to perform compensation movements in order to balance the barbell overhead.

Athletes perform warm-up and stretching exercises before any weightlifting activity. It has been shown in prior work [94, 95] that these preparations increase the range of motion (ROM) of muscles and joints. Stretching has also been shown to temporarily reduce peak muscular strength [96]. Therefore, many athletes are reluctant to perform prolonged stretching routines before athletic activities. There are stretching routines that focus on joint tendons and bands instead of muscular stretches with the goal of increasing ROM, but not affecting strength, e.g. [97, 98].
In this study, we compared the effects of a warm-up program with a stretching program focused on joints and muscles that are important for the examined weightlifting exercises. We assigned athletes into two groups: a warm-up group and a stretching group. The study design is visualized in Fig. 2.15. Prior to executing their preparation routines, all athletes were asked to perform 10 squats, 10 overhead squats and 10 front squats with a freely chosen weight while our system measured their weight distribution below the athletes’ feet.

Figure 2.15: Illustration of the procedures the participants went through. All subjects were tested in testing 1 with the barbell exercises. A randomly selected half of the athletes performed the warm-up, the other half performed the stretching. Afterward, all athletes were tested again in testing 2 on the barbell exercises.

Then, the warm-up group was given 10 minutes to perform a pre-defined regular warm-up consisting of rowing and body-weight movements. The stretching group was given 10 minutes to perform a tailored stretching program targeting hip and ankles (see Fig. 2.16). Finally, every athlete performed the same barbell exercises again while the sensor system acquired the pressure data. We analyzed statistical features of the COP in both groups, e.g., mean coordinates, variance, stability (defined as the fraction between standard deviation and mean of COP coordinates), etc.
13 athletes participated in the study: 5 female and 8 male of varying experience levels. Women used a 15kg barbell, men used a 20kg barbell. Where necessary, a coach instructed the athletes on the warm-up routines or the mobilization routines to ensure correct execution.

Our analysis revealed that both routines had statistical significant impact on COP features. The stability of, e.g., OHS exercise was affected significantly in the stretching group, but not in the warm-up group. The stretching group shifted the mean COP during the AS exercise significantly towards the toes (36.8 vs 39); the warm-up group shifted the COP in the other direction (29.8 vs 27.8). Both groups showed improved weight distribution during front squats and overhead squats, i.e. the mean COP shifted towards the heels.

Due to the small sample sizes and some individuals with exceptional flexibility, we could not draw a conclusive answer to the question what preparation routine is most beneficial to athletes. We could show, however, that our wearable pressure-assessment system was suitable for balance assessments in weightlifting athletes. Future research should focus on one single weightlifting exercise and at the same time increase the participant-pool size.
2.5 Conclusions

We developed a wearable, unobtrusive gait and balance assessment system that combined plantar-pressure sensors with an inertial measurement unit (IMU). The system allows long-term monitoring of more than 10 hours with typical settings; it continuously assesses features of balance of a standing person or gait features of a walking person.

In a study with elderly people, we were able to show that step timings acquired from a single IMU sufficed to discriminate between dual-task settings and single-task settings.

In a study with patients in rehabilitation, we showed that the combination of plantar pressure readings and inertial measurements can generate results from functional gait assessments that are in line with the assessments by medical experts. We showed also that balance assessments in standing subjects can classify between stable and unstable situations with more than 93% accuracy.

In a study with BPPV patients, we showed that the therapy affected the short-term stability of patients, but also (surprisingly) of healthy subjects.

We showed that movement timings of different body parts in weightlifters are a significant feature for discriminating between beginner and advanced athletes.

In a second study in weightlifters, we showed that a warm-up routine or a tailored stretching routine affected properties of the COP indicating an effect on the flexibility of lower-body joints, tendons and muscles.

2.6 Limitations

Regarding the hardware, we identified three limiting factors that need to be resolved in a future version. First, step width, similar to step length and duration, is a discriminative feature for assessing dynamic balance during walking [99]. The current implementation of PIMU cannot reliably estimate step width. IMU data suffer from noise that render estimations of distances between feet unreliable after short periods of time. A direct method to measure the distance between feet could resolve that limitation, e.g. by ultrasound time-of-flight measurements. The second limitation of the hardware is the limited bandwidth of the wireless ANT+ communication. Especially for weightlifting, but also
in static balance assessments, real-time visualizations of the pressure map would be favorable. The current hardware supports real-time transfers of low-dimensional features, e.g. COP creating a payload of 4 Bytes (2 bytes for $x$ and $y$ coordinates). The third limitation is the communication bottleneck imposed by the $I^2C$ bus connecting the pressure module with the IMU module.

Regarding software, in the synchronization experiment, a real-time assessment would be favorable to an offline processing of the data; especially if the sensor system was used as a feedback device for athletes.

Regarding the methods and results of the studies: as we showed in chapter 7 also healthy subjects showed an increased unsteadiness after liberation maneuvers – an unexpected result. To further investigate differences between patients and healthy subjects, a long-term analysis collecting data over several hours or days could create a better understanding of the differences between the two subject groups.

We learned from the analysis of the athlete-preparation study (see chapter 9) that flexibility is very individual. Some individuals showed superior flexibility compared to all other subjects. These subjects also showed limited effects of the interventions on the investigated features of COP. For future studies, either the sample size would have to be increased or a screening step would have to filter out subjects that show extraordinary performance (in both directions).

2.7 Outlook

A next version of the sensor should rely on wireless communication hardware that is able to process the data stream without any constraints. For example, Bluetooth Low Energy (BLE) is fast ($1\text{MBit/s}$) and also does not add significantly to the power budget. Typical BLE power requirements are $10.1\mu A$ (hardware-specified mean for RX and TX); typical ANT$^+$ consumption: $23.2\mu A$ according to [100]. Secondly, the hardware layout should be altered such that, e.g., the bandwidth limitations of $I^2C$ are avoided. Additional hardware is required to enable distance tracking between feet.

In weightlifting, the system should be evaluated as an unobtrusive feedback device using more subjects. Flexibility could be assessed for specific movements and the system could inform athletes about their performance. During training, the system could provide instanta-
neous feedback on exercise-specific parameters (COP, synchronization, speed, etc.). The above possibilities should be investigated in future studies.

In balance patients, especially BPPV, the system could be used to autonomously perform balance assessments over longer periods of time, e.g. multiple hours or days. A medical expert could use compiled results from logs to develop or support a diagnosis.
In this chapter, we present the pressure-sensing-IMU. Details of the hardware are provided, the firmware is presented and we also provide characterizations of various system properties.

This chapter was published in the IEEE Proceedings of the 8th International Conference on Intelligent Sensors titled PIMU: A wireless pressure-sensing IMU [65].
3.1 Abstract

Inertial measurement units (IMU) are included in uncountable consumer electronic products, e.g. smart phones. IMUs are state of the art for research in human motion analysis, context and activity recognition. Sensor setups to estimate the activity of a subject, e.g. standing, sitting, walking, climbing stairs etc., typically require a multitude of sensor nodes to provide reliable estimations. In our paper, we present a sensor system for enhanced context and activity recognition while requiring a minimal set of sensor nodes. Our system combines a pressure sensor featuring high spatial resolution (1260 sensitive points) with an IMU. The pressure sensor is typically placed inside a shoe and measures the force exerted on the feet. Our system eases the detection of many situations: differentiating between sitting and standing, walking and climbing stairs etc. It is adjustable to virtually any shoe and therefore could be included in projects requiring specialized footwear (e.g. running, weightlifting or biking shoes). Data can be stored on the sensor node or it can be transferred wirelessly to a remote aggregator device, i.e. a device responsible for data stream reception, sensor control and analysis. The aggregator can be implemented in a smart phone or a PC. Our system can in real-time detect situations of sitting, standing and walking automatically. The system’s low-power implementation allows for run-times exceeding 14 hours. In a multi-system setup the systems can be synchronized with a node-to-node offset in the order of \(10\mu s\). The pressure can be sampled at a maximum of \(100\, \text{Hz}\), the inertial data is available at a rate of \(512\, \text{Hz}\). Our small-footprint real-time classifier can distinguish between the situations standing, sitting, and walking with an accuracy above 99%.

3.2 Introduction

Often the problem of detecting a movement feature reliably or estimating an activity robustly is tackled by increasing the number of sensor devices. For example, in human movement analysis, the problem of distinguishing between a subject standing and sitting can be solved by attaching four sensors to her legs: one on each shin, one on each thigh. Using the attitude of the four sensors, a classifier could differentiate between the two situations. For lab settings this usually does not present a substantial problem since sensor-installation overhead
is not crucial. Things look differently if a system is targeted for long-term or unobtrusive monitoring. Comfort in wearing is an important issue, but also a small number of sensors is favorable. Experience has shown that the success of a long-term monitoring project depends on the ease of setup if the subjects have to use the system autonomously. One way to alleviate this problem is to switch to different sensor modalities, e.g. cameras. However, privacy concerns quickly arise and – important from a scientific viewpoint – the system is restricted to a given environment where the cameras are installed. As soon as the subject leaves the purpose-built infrastructure the systems stops working. So, for all practical purposes, a system that requires an environment to be adapted can be looked at more as an extension of the lab, than as real life.

In this paper, we present an unobtrusive (integrated into one or two shoes) and pervasive (high grade of information acquisition) sensor system that is suitable for long-term monitoring projects. We require neither a specific infrastructure nor a dedicated setup procedure. Our system is tailored to movement analysis involving lower leg and feet motion. An IMU module samples and processes 3D inertial data from an accelerometer, a gyroscope and a magnetometer. A pressure module samples and processes force readings exerted to 1260 sensor points. Our system can be integrated virtually transparently in a shoe of any size. The system can store raw data or processed data (e.g. features) onto a internal storage device for later use. However, it is also capable of forwarding the data to a remote aggregator device like a smart phone or a PC. Inertial data can be processed or stored at 512Hz, pressure data is available for processing at more than PressureHZ.

The remainder of this paper is organized as follows: in section 3.3 we provide an overview on alternative systems for gait analysis at various levels of resolution. In section 3.4 the system modules are described and we present the principle of operation. In section 3.5 we present our evaluation procedure for our system and its individual modules; power consumption, speed, accuracy etc. In section 3.6 we present the results of our evaluation and, finally, we draw conclusions and provide our vision for the future in section 3.7.
3.3 Related Work

An early approach of assessing and classifying gait properties using objective means is presented in Liston et al. [101]. They used a walkway enhanced with sensory means in order to measure the features "step length", "width of base" and "equilibrium". The authors investigated pathological gait features that are caused by damage of different brain areas. Their system consisted of two infrared barriers, the subjects had to wear an infrared detector, a data logger and foot switches to detect the steps. The step width was measured using ink attached to the subjects' feet that left visible footprints on the floor.

Webster et al. [102] introduce the GAITRite sensor system used for the evaluation of walking performance [81]. This sensor system consisted of a pressure sensitive mat in various sizes. The largest model was about 1 m wide and 7.5 m long, allowing for the analysis of step length, step width and frequency. Webster et al. compared the system's performance to a state-of-the-art optical 3D motion tracking system, e.g. VICON.

Kang et al. [103] used a system relying on tri-axial accelerometer data. Their intent was to develop an automatic human movement classification system using a single waist-mounted accelerometer. They targeted the elderly population as users for their system, but only young people have been used in their evaluation.

A large system of wirelessly accessible sensor populations (WASP) was presented in Atallah et al. [104]. They developed a service-based architecture for pervasive monitoring of elderly using both ambient and wearable sensors. Various components are described, e.g., body sensor networks, ambient sensor networks, a personal mobile hub (data collection, emergency trigger), wireless sensor hub (to relay data to off-site components), remote data collector etc. Ambient sensors comprise video cameras, reed-switches in doors or appliances, microphones, pressure sensors. Wearable sensors comprise invasive technologies such as heart monitoring sensors, oxygen saturation sensors, acceleration sensors etc.

In [105, 106, 107] mobile systems were presented for measuring basic force distributions (amongst other modalities) on feet. The devices were used for abnormality detection in gait or for fitting prostheses. However, they required a tethered connection to a computer or to a hip-attached device.

Paffen et al. [34] created a mobile version of a pressure sens-
3.4. System Description

Our system consists of four components: an IMU module, a pressure-acquisition and processing module (c.f. fig. 3.1a), the pressure sensor (sole shape, seen in fig. 3.1b) and a remote device (a PC or a smartphone with ANT+ capabilities [110]); all components are illustrated in fig. 3.2.

Frenken et al. [108] focused on detecting the event of a subject rising from a chair and walking five meters: the timed up-and-go test (TUG). The authors relied on ambient sensory equipment to perform TUG in an automated way. The authors developed a tailored chair with pressure sensors, infrared light barrier senders and receivers, a control box, and a laser range scanner.

Harms et al. [109] developed a small wireless sensor system combining IMU sensors onto a small footprint. The system’s autonomy enables various project to record and analyze motion data virtually independent of the environment.

3.4 System Description

fig. 3.1: The PIMU system overview.

(a) Plantar-pressure sensor board.  (b) PIMU; Sensor board inside casing (green box).
The pressure sole combines 1260 force sensing resistors (FSR) in a matrix arrangement. It is manufactured by TekScan and has been modified to be applicable for our system. The IMU combines an accelerometer, a gyroscope and a magnetometer that sample three spatial dimensions at up to $512\text{Hz}$. The pressure module is connected to the FSR matrix in order to access and sample each FSR individually.

### 3.4.1 Hardware Modules

With a size of $14 \times 45 \times 4\text{mm}^3$, the IMU module uses a dsPIC33F-series micro controller by Microchip as MCU (micro controlling unit). The system runs at $40\text{MHz}$ using a PLL circuitry. The micro controller communicates over $I^2C$ to the 3 inertial sensors and the pressure sensor. Communication to a radio module (ANT+) is performed via UART. A SPI bus connects the micro controller to an SD-card reader. The accelerometer internally samples acceleration at about $2\text{kHz}$ in three dimensions. The gyroscope samples 3D rotation rates at $1\text{kHz}$ and the magnetometer reports magnetic field strength every $20\text{ms}$ ($50\text{Hz}$). The UART channel features $57600$ baud, SPI and $I^2C$ are running at $400\text{kbps}$.

A 16-bit micro controller builds the heart of the pressure sensing module. The physical dimensions of the sensor board are $43 \times 43 \times 3\text{mm}^3$. The MCU features 32 ADC inputs that can be sampled at $1\text{Msample/sec}$. We aimed at creating a system with a small PCB footprint that provides a relatively large number of ADC inputs in order to keep the circuit-board layout simple and the number of components small. The trade-off had to be made between a small chip packaging (additional components required (e.g. a multiplexer)) and a larger packaging but no additional components. The FSR have a large impedance - in the order of $5\text{M}\Omega$ if no force is applied. To fully exploit the sampling speed of the ADC module, we used for each input channel an Op-Amp enabling shorter conversion times.

The third module of our sensor system is an array of multiple FSRs [111]. The individual FSRs are sandwiched in between two flexible polymer sheets arranged in a grid order. Flexible conductive connections are present on each side of the sole: on one side in a column-like order, on the other side in row-order. Since each FSR combines a diode circuitry that reduces the cross-talk between two adjacent rows or columns it is possible to address every FSR in the sole by selecting its row and its column. There are 1260 FSRs present on the sole and
we are addressing $1248 = 32 \cdot 39$ of them. The ADC module of the pressure sensors samples with 10Bit resolution, however, we discard the lowest two bits resulting in one byte per FSR reading. Hence, a complete instance of a sole contains 1.248kB.

Sampled data can be streamed wirelessly to a remote device, e.g. a smart phone or a PC - the so-called aggregator. The remote device also has the role of a controller: if multiple sensors are present, it allows for synchronized sampling and controlling of the sensor devices. It communicates to the sensor nodes using the ANT+ protocol. We used a smart phone by Sony, an Experia S, that features a built-in ANT+ chip. We programmed an Android application and implemented a network stack together with a communication protocol that allowed us to control sensors remotely. Our system also enables us to receive real-time feedback from any sensor.

### 3.4.2 Principle of Operation

Configurations for the IMU module can be defined using a terminal tool and connecting the sensor device via USB to a computer. Sampling frequency, storage options and wireless parameters are defined this way. If wireless communication is enabled the sensor device can be
fully controlled using, e.g., a smart phone. This way it can also stream in real-time sampled data, however only at a limited bandwidth due to the properties of the ANT+ protocol. At start-up, the sensor initializes the IMU sensors, sets up the communication to the ANT+ module and reads configuration values from the SD-card storage. We denote this configuration tuple as a profile. The sampling rate defined in a profile dictates the frequency the MCU reads fresh raw data values from the IMU sensors. Internally, the IMU sensors sample at a maximum speed. Regularly, a buffer of sampled IMU sensor values is written to the SD card. On request, the node transmits the newest reading via ANT+ to a remote aggregator.

The ANT+ standard defines two modes: master or slave mode. In master node, a device transmits at a given frequency beacon messages that can be received by a slave node. ANT+ is a time division multiple access-inspired protocol with time-slots not shorter than $5\text{ms}$. In master-mode a node transmits at a given periodicity beacon packages possible slave nodes can answer to. It is by design of the protocol that no two master nodes can send at the same time, but need to interweave their packages. This reduces directly the bandwith of the channel. We required for our system that an arbitrary number of sensor devices can run at the same time and be controlled remotely. Hence, it was not an option to enable the master mode on the nodes: with every additional node the reaction time of the communication would have become worse and the communication protocol would have been much more complicated. Also, synchronization of multiple nodes would have been more difficult. Instead, we decided to setup all sensor nodes are slaves, i.e. they listen to a single aggregator. That device regularly transmits beacon messages or issues commands. These commands can be broadcast to all nodes, e.g. "start sampling". However, our network stack also features addressed messages that allow us to control a single node or set of nodes. We use the addressed format to stream IMU data to the aggregator: When the master device needs fresh data it requests an update from a specific node.

At start-up, the pressure module initializes all components: timers, communication and in- and outputs. As can be seen in fig. 3.2, the pressure sensor board communicates to the IMU sensor board (from now on referred to as \textit{IMU}) via $\text{I}^2\text{C}$. After initialization, the IMU configures communication parameters with the pressure board. At maximum
speed the pressure sensor samples an entire sole at about 120Hz.

\[
120\text{Hz} \times 1248\text{Bytes} = 146.24 \text{ kByte} \cdot s^{-1} \\
= 1198080 \text{ bit} \cdot s^{-1}
\]

As the \( \text{I}^2\text{C} \) bus runs at 400kbps, the pressure sensors’ data rate exceeds the bus bandwidth by about a factor of three. However, since it is a shared channel, communication to the IMU sensors take up some bandwidth, too. We have multiple strategies to cope with this issue. The most intuitive one is to transmit as fast as possible a complete set of pressure samples, e.g. 1248 ADC readings: mainly due to \( \text{I}^2\text{C} \) limitations, we need at least a \( 16^{th} \) of a second to transmit a complete set of readings from the pressure sensor to the IMU. In order to increase time resolution, we can trade spatial resolution by applying a compression scheme: depending on the required sampling rate, we only transmit a size-reduced version of the data by applying an \( n \times m \) compression. At the same time this introduces a low-pass filter and smoothes the data even further to the already down-sampling (discarding two bits).

The most aggressive data reduction scheme is to calculate features of interest on the pressure sensor and only transmit these values. So far we have implemented the features {"mean", "maximal pressure patch", "principal axis") and also statistical features on the mean value computed within a window of 1 second. Please consult section 3.4.3 for a detailed description.

One side of the pressure sole is connected to the ADCs of the MCU (indirectly through the operational amplifiers, Op-Amp. Cf. fig. 3.2), the other side connects to the digital IOs. Our data acquisition algorithm iterates through each digital IO pin. At every given moment only one digital input has voltage applied to - all others are tied to ground. While a specific pin is tied to VCC, each ADC is sampled and converted. As soon as a vector of ADC values has been acquired, the current output pin is tied to ground and the next pin is enabled.

### 3.4.3 Feature Calculation

Our system has sufficient computational power to calculate the features presented below on the MCU and in real-time. The critical part was the limited availability of RAM, however, we have addressed that issue by creating algorithms with small memory-footprints.

The definition of the “mean pressure”, \( \mu_p \) is intuitively clear; it is the mean of all ADC readings, rounded to the next byte value. Its transmis-
sion to the IMU can proceed at maximum sampling speed (120Hz). Let $S_{FSR}$ be the $32 \times 39$ array containing the readings form the ADC. Then,

$$
\mu_p := \frac{1}{1248} \sum_{r \in \text{rows}} \sum_{c \in \text{cols}} S_{FSR}(r, c)
$$

The calculation of the second feature, "peak of pressure" needs a pre-processing step. Due to the soft tissue of the feet, the correlation between a single FSR to all its neighbors is relatively high (we will quantify it in section 3.6). Hence, we apply a first a spatial smoothing step (Gaussian filter, $Gauss(.)$), then a compression step $Downsample(.)$ and finally we calculate the maximal pressure patch. This pre-processing creates a more robust feature not subject to spatial noise. The peak of pressure is a three-byte tuple, $pop := \{x, y, v\}$ the $x$ and $y$ coordinate as well as the value at the center. Below we describe the procedure: First, a smoothed and down-sampled version of the readings is created, e.g. $\tilde{S}_{FSR}$. The peak-of-pressure coordinates are defined as the indices $k$ and $l$ at which $\tilde{S}_{FSR}$ is maximal. The pop-value, hence, is the smoothed and downsampled reading at the coordinates $(x_{pop}, y_{pop})$.

$$
\tilde{S}_{FSR} = Downsample\left(Gauss\left(S_{FSR}\right)\right)
$$

$$
(x_{pop}, y_{pop}) = \arg \max_{k,l} \left(\tilde{S}_{FSR}(k,l)\right)
$$

$$
v_{pop} = \tilde{S}_{FSR}(x_{pop}, y_{pop})
$$

The notion of the "principal axis" is motivated by a principal component analysis (PCA, [112]) in the pressure space. However, some pre-processing needs to be performed. Due to the noisy nature of the ADC readings, we need to apply a smoothing step. Mainly to save calculation time, we use a binning approach where we divide the possible values in range $[0, 2^8 - 1]$ into 25 bins. I.e. each value in $S_{FSR}$ is assigned a bin. Let $\bar{S}_{FSR}$ be the binned version of $S_{FSR}$. We then iterate through all values in $\bar{S}_{FSR}$ and remember to what bin it belongs to. Our bin structure is an array of length 1248 containing 3-byte elements. Our definition drastically reduces storage needs ($3 \times 1248$ bytes) compared to the trivial approach of creating a structure of size $25 \times 1248$ bytes. In its initial state, the bin structure can be described as follows:

$$
BIN(i) = \begin{cases} 
\{i, 25\} & \text{if } i \in [0, 24] \\
\{idx, next(i)\} & \text{if } i > 24
\end{cases}
$$
Every element in $BIN$ is a structure that contains an index into $S_{FSR}$ and an index to the next free slot in $BIN$. To collect all indices of $S_{FSR}$ for a given bin $k$, the algorithm has to start at $BIN(k)$ and follow the links until all elements have been collected. Fig. 3.3 provides an illustration on the structure for a state where the algorithm as fed the first three values for bin zero. The box represents a list element. The left item is the index to $S_{FSR}$, the right part is the index to the next element. The numbers below the boxes represent the index of the $S_{FSR}$ array.

![Figure 3.3: Illustration of the BIN structure: In $S_{FSR}$, the elements with index 7, 22, and 31 were assigned to slot zero.](image)

Next, we identify the non-empty bin with the largest BIN values containing more than 5% of the samples (5% gave the most robust results and it is sufficiently large to not suffer from outliers). For that bin, we calculate the connected components and verify if the largest connected component still fulfills our size requirements. If so, the coordinates in that bin are the input to the PCA. Finally, the output of the PCA is a two-dimensional vector, representing the pressure patch with the highest value.

Pressure sensors provide a more direct way for gait analysis than, e.g. acceleration data, since they measure directly the physical features rather than a derivative. We have implemented a real-time algorithm for gait analysis which, in the current state, detects situations of standing, sitting and walking, but will be extended to also estimate features like stance and swing time. We use a support vector machine (SVM, cf. [113]) as a classifier for discriminating between the three aforementioned situations. The support vectors were calculated offline and then written to the sensor.

### 3.5 System Evaluation

We evaluated our system bottom up: from basics to higher-level functionality.

Power consumption: current requirements of the IMU at various sampling frequencies as well as the energy needs of the pressure sen-
sor were measured. We connected the system to an external power source that allowed us to sample the current drawn for 10 seconds.

Speed: the IMU's task is to sample exactly at a given rate, whereas the pressure boards purpose is it to sample as fast as possible. We evaluated both systems regarding sampling speed.

Synchronization: we evaluated the synchronization between two sensor nodes by connecting them rigidly to each other with tape. Then, we started sampling using our remote control device. Next, we exposed the two sensors to the same external force, i.e. multiple acceleration peaks. The synchronization offset was later calculated in MATLAB by comparing the temporal differences of the two signals.

Accuracy and linearity: The accuracy of our pressure sensor was measured using an strain and force sensing device. We selected a FSR sensor on the sole sensor and applied 10 sweeps from 0 N to 40 N with our sensing device.

Pressure characterization: we calculated the correlation coefficient for the idle pressure sole; this value provides an indicator on the performance of the diodes in removing cross-talk. We used the results from the linearity-test setup and calculated the correlation matrix for a sweep with the force sensing device from 0 – 40 N. We extracted a 3 × 3-patch from the pressure samples with the tested point in the center. We then calculated the correlation matrix for each of the 9 FSR points to all others.

Feature computation: we analyzed the feature calculation for the peak of pressure and principal component in terms of speed restrictions especially for real-time feedback. Our algorithm for feature calculation was developed in beforehand with MATLAB and then transformed to C-code. The logic is exactly the same and we do not expect any differences in accuracy.

Classification accuracy: we have recorded 10 sessions of a subject walking, sitting and standing. A subset of the data was used for training the SVM and we optimized the parameters using 10-fold cross-validation. Later, the performance of the classifier was evaluated using data not yet presented to the classifier.
3.6 Results

3.6.1 Power Consumption

We analyzed the power consumption for multiple sampling frequencies of the IMU and the sole sensor. The operating system tried to save power as much as possible and it puts the CPU in idle mode if it was not needed. Hence, the required energy directly depended on the sampling frequency.

<table>
<thead>
<tr>
<th>Freq.</th>
<th>(ANT+)</th>
<th>Current (mA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16Hz</td>
<td>no</td>
<td>28.93 (±0.16)</td>
</tr>
<tr>
<td>16Hz</td>
<td>yes</td>
<td>31.92 (±0.17)</td>
</tr>
<tr>
<td>32Hz</td>
<td>no</td>
<td>28.94 (±0.15)</td>
</tr>
<tr>
<td>32Hz</td>
<td>yes</td>
<td>31.94 (±0.17)</td>
</tr>
<tr>
<td>64Hz</td>
<td>no</td>
<td>33.32 (±1.01)</td>
</tr>
<tr>
<td>64Hz</td>
<td>yes</td>
<td>40.40 (±1.10)</td>
</tr>
<tr>
<td>128Hz</td>
<td>no</td>
<td>34.70 (±1.94)</td>
</tr>
<tr>
<td>128Hz</td>
<td>yes</td>
<td>41.77 (±2.07)</td>
</tr>
</tbody>
</table>

(a) IMU power consumption

Table 3.1: Power consumption for the two sensor systems at different configurations.

<table>
<thead>
<tr>
<th>Freq.</th>
<th>Current (mA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idle</td>
<td>27.07 (±0.088)</td>
</tr>
<tr>
<td>16Hz</td>
<td>30.49 (±0.83)</td>
</tr>
<tr>
<td>32Hz</td>
<td>33.69 (±0.90)</td>
</tr>
<tr>
<td>64Hz</td>
<td>39.12 (±0.64)</td>
</tr>
<tr>
<td>120Hz</td>
<td>49.19 (±0.17)</td>
</tr>
</tbody>
</table>

(b) Pressure sensor power consumption

3.6.2 Speed and Temporal Characteristics

The IMU allowed sampling frequencies up to 512Hz if writing to SD storage was enabled. In stand-alone mode, i.e. without the pressure subsystem enabled, sampling speeds up to 1024Hz were feasible.

We evaluated the synchronization accuracy between two sensors if sampling was triggered via ANT+. Synchronization offset between two nodes were in mean \( \mu_{\text{sync}} = 10.1 \mu\text{sec} \) with a standard deviation \( \sigma_{\text{sync}} = 2.3 \mu\text{sec} \).

3.6.3 Pressure Sensor Characteristics

In fig. 3.4a, we see the correlation matrix for a 3 × 3-patch around the FSR we used for linearity characterization. We can see that the FSRs right next to the central sensor suffer from crosstalk with an absolute correlation value of about 0.75. Note that the crosstalk between FSR 1 and FSR 5 is induced by pressure probe that was slightly too large for a single FSR and it therefore touched FSR 1.
Chapter 3: PIMU: A Wireless Pressure-Sensing IMU

**Figure 3.4:** Characteristics of the pressure sensor system: cross-talk on the left side and linearity on the right side.

In fig. 3.4b, the reconstruction of a linearly applied force from 0 – 40N is shown. The sigmoidal function shape is clearly visible and we fitted a sigmoid function template, e.g.,

$$f(x) = \frac{a}{b + c \cdot e^{-d \cdot x}}$$

to the data using the Levenberg-Marquardt algorithm for non-linear optimizations. We could fit to the data a sigmoid with a RMS value of 0.8742. The parameters for our models are \(\{a = 0.406, b = 0.009, c = 1.672, d = 0.002\}\).

### 3.6.4 Pressure Feature Characteristics

Speed of computation was not an issue for all features; "mean", "peak of pressure" (POP), and "principal axis (PA) were all computed at maximal speed, e.g. at most 100Hz.

In Fig. 3.5 we show the result of our peak-of-pressure calculation. Fig. 3.5a is a subset of a complete data sample where the pressure contains a maximum. The sensor board calculated in real-time a smoothed version of the patch and also the center, both are shown in fig. 3.5b.
3.6. Results

(a) Raw pressure data patch.  
(b) Smoothed data with centroid.

Figure 3.5: Algorithm output for finding the peak of pressure.

Fig. 3.6 illustrates the data flow from raw values to a representation of the principal pressure axes. Fig. 3.6a is an example input to our algorithm. For illustration purposes, we only display a sub-sample of the complete pressure data set. In a first step, the data was smoothed, as shown in fig. 3.6b. We then applied the binning approach which resulted in a smaller subset of valid values. On this subset of coordinates, we calculate the principal components. Fig. 3.6c shows the binned data set as well as the calculated principal components in red.
3.6.5 Classification Characteristics

Our classification algorithm for discriminating between standing, walking and sitting episodes needed the accelerometer magnitude and mean pressure as features. The feature on the accelerometer’s magnitude was calculated within a 500ms window, the pressure-mean feature was first input to a 500ms windowing prior to being fed to the classifier. The class boundaries are intuitively clear: walking is high mean pressure and high accelerometer magnitude. Standing differs from walking as accelerometer magnitude is low. Sitting shows medium or low pressure mean with low accelerometer magnitude. [Fig. 3.7] illustrates a sample episode where the subject was first sitting on a chair, rised, walked some steps, stopped, walked again and finally sat down. Our classifier detects the situations 99.346% correctly.
3.6. Results

Figure 3.7: Superimposing magnitude vector of accelerometer (sampled at 128 Hz) with mean values of pressure sole (sampled at 100 Hz).
3.7 Conclusions and Outlook

In this paper, we introduced a mobile pressure and inertial measurement unit, PIMU. Thanks to its adaptivity, it can be integrated in virtually any shoe, opening new opportunities for real-time, but also for long-term monitoring. We motivated the importance for a wireless communication link by introducing the notion of a real-time control and feedback device usable in arbitrary environments and we provided an implementation. We showed that various features in pressure space, e.g. peak of pressure or principal axis can be calculated at high speeds. We characterized the response of the FSR sensor sole and thereby illustrated the feasibility of storing absolut pressure values. Our system detected situations of standing, sitting and walking with an accuracy of over 99%.

We are going to use this system in different settings, such as elderly care, context and activity recognition, gait analysis in general, but also sports-related.
In this chapter, we present internals of the firmware of PIMU. Since the communication between the pressure module and the IMU module is too slow for real-time transfer of pressure data, a compression step was implemented on the pressure module. We present the data pipeline from compression on the embedded sensor until reconstruction on a PC.

This chapter was published in Body Sensor Networks, 2014 titled Enabling high-speed data acquisition with compressive sampling [66].
Chapter 4: Compressive Sampling

4.1 Abstract

We augmented an existing inertial measurement unit, IMU, with a secondary module sampling at high speeds (100Hz) an array of 1260 force sensitive resistors (FSR) embedded in a flexible, thin plastic foil. Due to legacy imposed by the existing sensor platform, we were confronted with severe bandwidth restrictions on the I2C channel between the two modules. The secondary module created data at about 1.2MBit/s, however the I2C component of the IMU had an upper limit of 400kBit/s. Communication between the two modules was necessary as storage and wireless communication were only available on the IMU module. Since altering the existing system was not an option, we looked for ways to reduce the bandwidth requirements while at the same time maintain the core functionality of the secondary module. We present in this work our analysis of a Compressive Sampling (CS) solution for our sensor setting. We tested variations of CS and present their performances. To increase sparsity in the input data, we applied a differential encoding scheme on the data frames. The original CS algorithm was applied to the difference frames without further pre-transformation. We also tested the performance of a Wavelet-transformation step. Finally, we implemented on the embedded sensor platform a differential encoding scheme without pre-transformation and thus reduced the bandwidth requirements to about 30% of the original demands.

4.2 Goals

We attached a secondary sensor module to an existing inertial measurement unit (IMU). This secondary module sampled at high speeds of 100Hz 1260 force sensitive resistors (FSR). The FSR were embedded in a flexible plastic foil that could easily been integrated in shoes. The secondary module allowed us to accurately reconstruct the weight distribution of subjects standing or moving on their feet. For our research, it was important to have an accurate estimation of a subjects' pressure distribution below their feet. Due to limitations imposed by the primary module (limited bandwidth of the communication channel, I2C), the dependency on the primary module (it contained wireless communication and storage), and lastly due to the fact that we could not replace the primary model, we faced the task of data reduction on the secondary module. A significant advantage over related
systems was our system’s high spatial (1260 sensing points), and high temporal resolution (100 Hz). To exploit the potential of the system, temporal or spatial sub-sampling was not an acceptable option. Also, advanced loss-less compression algorithms \[82, 83, 84\] were not usable due to the limited computational resources of the embedded systems. Hence, we aimed at a data compression scheme that was of low computational complexity at the compressing site (sensors). Further, data recovery needed to be of low error. We did not require loss-less compression, but characteristics of the data were required to be conserved. The system we developed was not required to feature real-time reconstruction. Rather, we allowed an arbitrary reconstruction time, because this task would be performed on a desktop computer after data acquisition. In this work, we briefly present the hardware characteristics of our sensor system. For more detail cf. our previous publication describing the system [65]. We present the methods used for data reduction and reconstruction. Further, we propose a feature-centric error metric and evaluate the CS-pipeline according to it. We characterize the performance of our system with offline and real-time data.

### 4.3 Methods

The IMU module featured a 16-Bit Digital Signal Controller (DSC) by Microchip clocked at 16 MHz, a wireless transmission component (implementing the ANT+ network stack) and a physical connection to SD cards used for storage. Communication to inertial sensors used I2C. For storage, data were transmitted using an SPI channel. The secondary module was attached to the I2C bus. The secondary module used a Micro Controller Unit (MCU) by Microchip and sampled 32 analog-to-digital converters (ADC) at 125kSample/s. The FSR were organized in a matrix structure and with the proper connection asserted by a scan-line sampling algorithm, the MCU sampled all 1260 FSR with its 32 ADC [65]. Communication between the two modules was following the master-slave principle where the IMU acted as a master, requesting sensor data, and the secondary module acted as the slave device, reporting data. The DSC limited the speed of the I2C to 400kBit/s while the secondary module reported data at 126000Byte/s = 1008000Bit/s. Thus, the bottleneck is evident: transmission of a full sample between the two modules would result in a
sampling rate of \((400000 \text{Bit/s})/(1260 \cdot 8) \text{Bit} = 39.7 \text{Hz}\). Therefore, one frame would require about 25\(\text{ms}\) to be transmitted between the modules – approximately a factor of 2.5 slower than the sampling rate of the secondary module. Thus, we needed to reduce data size to about one third for real-time transmission.

In Compressive Sampling [85], values \(x\) are projected from a high-dimensional space onto lower-dimensional representations \(y\) by a projection step with a random matrix \(A\) (also see fig. 4.1):

\[
y = Ax. \tag{4.1}
\]

![Figure 4.1: In the compression step, original data are sparsified and then multiplied with a pseudo-random sampling matrix to create the new representation.](image)

The value \(x\) is required to be sparse [114] to allow good reconstruction. Recovery of the original data is achieved by convex optimization where an over-determined system of equations is solved under the constraint that the estimate of \(x\), \(\hat{x}\), be sparse as well (also see fig. 4.2):

\[
\arg\min_{\hat{x}, A\hat{x}=y} \|\hat{x}\|_{L^1}. \tag{4.2}
\]
An initial analysis of our data revealed that they were sparse by nature. Further, differences between two consecutive data frames were sparse and of low rank. We therefore implemented a differential preprocessing step where only every 100th frame (to limit error propagation; representing 1 second) was forwarded directly to the CS pipeline. From the frames in between we calculated difference frames, $d_i$ (see fig. 4.3), that were defined as the difference between the current data frame $f_i$ and its predecessor $f_{(i-1)}$:

$$d_i = f_i - f_{(i-1)}$$ (4.3)
The first steps of the Compressed-Sampling pipeline were mathematical transformations to possibly increase sparsity even more. We tested the identity transform (i.e. relying on the sparsity of the original data) and Wavelet transformations. The projection step \( y = Ax \) was done using a random matrix \( A \) effectively reducing the size of the data, because \(|y| << |x|\). Reconstruction was implemented in MATLAB using "Basis Pursuit" as an optimization strategy. For offline testing, we used the root-mean-squared (RMS) error as a metric:

\[
E_{\text{sim}}(\tilde{x}, x) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\tilde{x}_i - x_i)^2},
\]

with \( N \) being the size of the source data, i.e. 1260. The error \( E_{\text{sim}} \) represented the RMS error between all sensing points of two frames, i.e. the original and the reconstruction. The unit of the RMSE are force-per-area (\( F/A \)) readings, e.g. pressure values. However, we did not calibrate the sensor foil – therefore \( E_{\text{sim}} \) is a unit-less value within the range of \([0 – 255]\).

We assessed \( E_{\text{sim}} \) on 100 frames (or 4 seconds) from an arbitrary sample set acquired earlier. Note that these data were of low-speed acquisition, e.g. the sampling rate was 25Hz. We calculated the com-
pressed version in MATLAB and compared the reconstruction thereof to the original data.

For our application, we were mostly interested in calculating the center-of-pressure (COP) of a standing subject. The COP is a proxy to the reaction forces between a subjects’ feet and ground. We estimated the COP with a rigid-plate model by calculating the net-torque applied by a subject with her feet. The COP is a two-dimensional vector representing the coordinates of the center of the reaction forces. We required the CS pipeline to maintain the characteristics of the data such that COP calculations were not disturbed.

To validate the CS pipeline "in-the-wild", we calculated the COP on the secondary module on raw data, $COP^{(2nd)}$. The compressed representation was then calculated and transmitted to the IMU module along with $COP^{(2nd)}$. After reconstruction, we calculated the COP on the deflated data, $COP^{(rec.)}$ and compared the two values:

$$E_{real} = \sqrt{\frac{1}{2} \sum_{i=1}^{2} \left( COP^{(2nd)}_i - COP^{(rec.)}_i \right)^2}$$  \hspace{1cm} (4.5)

$E_{real}$ is the RMS error between the two coordinates. The units of $E_{real}$ are coordinates or mm, as one coordinate increment represents 5mm.

### 4.4 Results

Data values were 8-Bit and thus in the range of [0-255]. We calculated for each of the 100 frames $x_i$ the compressed representation $y_i$ and calculated an estimate $\hat{x}_i$ of the data using convex optimization. In table 4.1 the results for the different transforms are shown.

<table>
<thead>
<tr>
<th></th>
<th>$E_{sim}$</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>No transformation</td>
<td>3.6418</td>
<td>$\sim 20%$</td>
</tr>
<tr>
<td>Wavelet transform</td>
<td>1.1208</td>
<td>$\sim 7%$</td>
</tr>
</tbody>
</table>

**Table 4.1:** Error statistics for 100 frames with differential data as input. CR is the percentage of the size of the data after compression relative to raw data size.

The trivial approach without a transformation step resulted in a RMS of 3.64 calculated over all 1260 values. We designed the random projection matrix $A$ to achieve a compression ratio of 80%, thus
requiring only a fifth of the original bandwidth. As shown in Table 4.1, the Wavelet approach reduced the RMS even further to 1.12 while only requiring to transmit 7% of the original amount of data.

For the Wavelet approach, we split each input frame (either a raw or a difference frame) into two \((30\times20)\)-sized patches. We embedded these data in two zero-initialized patches of dimensionality \((32\times32)\) due to requirements of the Wavelet algorithm. Further, the Wavelet transform (WT) was applied and we used the 10% most important coefficients of the transform. The projection step reduced data size by another 30%. The first step of the reconstruction recovered an estimate of the WT, then the inverse WT was applied and the appropriate parts were extracted from the two \((32\times32)\) patches.

\[
\begin{array}{|c|c|c|}
\hline
\text{No transformation} & 0.302 & 30\% \\
\hline
\end{array}
\]

Table 4.2: Real-world error characterization. CR is the percentage of the size of the data after compression relative to raw data size.

The computational requirements of the WT were prohibitive for being used on the secondary module, unfortunately. We therefore decided to implement the simple approach without a transformation step, using the differential frames. In Table 4.2, the results are shown of evaluating \(E_{\text{real}}\) on 1 minute of data. The mean of \(E_{\text{real}}\) on \((60\cdot100) = 6000\) frames was 0.30 coordinates. This means that the RMS error between COP coordinates calculated on original data and the coordinates calculated on inflated data was about \(1.5 \text{mm}\), since one FSR was roughly \(5 \times 5 \text{mm}\) in size. We have chosen the size of the random matrix \(A\) such that a compression rate of 70% was achieved, thus transmitting 30% of the amount of that of the original size which was enough to allow real-time data transfer.

### 4.5 Conclusion and Outlook

In this work we presented the simulation and real-world implementation of different compression schemes inspired by Compressive Sensing (or Compressive Sampling). The tradeoff between increased computational complexity on the acquisition module and reduced compression rate lead us to the implementation of a differential encoding where
sparsity is created by calculating the differences between two consecutive data frames. As data was expected to change slowly between two consecutive frames, the difference frames exhibit a better sparsity than the original data. Our results support [85] as reconstruction errors were low with a normally distributed sensing matrix $A$. The error introduced by the reconstruction did not affect the feature calculation. Feature errors $E_{\text{real}}$ were low and did not affect further data processing in any case. By increasing the effective frame rate to the original sampling speed we were able to calculate meaningful feature even for data previously not usable to us. Especially, time-domain analysis could benefit from the increased number of frames available.
In this chapter, we present the results of a study evaluating the effects of dual tasks on gait features in elderly subjects. Our approach was to use a minimal number of sensor devices: we showed that a single IMU suffices to detect abnormalities in gait with high probability.

This chapter was published in MobiHealth, 2012 titled One IMU is sufficient: A study evaluating effects of dual-tasks on gait in elderly people [67].
5.1 Abstract

In industrialized countries the share of elderly subjects is increasing. Hence, diseases or symptoms associated with aging are more common than they were in the past. As a consequence, more effort is invested into research analyzing the effects of aging on motion and cognition. However, economical and flexible methods to measure motion and its cross-effects with cognition are still missing. Therefore, we developed a new approach which neither requires a specific location, large infrastructural requirements, nor does it require large investments. We base our setting on match-box sized inertial measurement units (IMUs) attached to the participants’ legs. 47 elderly subjects participated in our study where we analyzed the interplay between cognitive load and gait features. We show that it is feasible to automatically detect episodes of interest, e.g. straight path, during walking periods of a subject only using IMU data. Our approach detects the steps autonomously and calculates gait features without supervision. The results demonstrate that cognitive load induces a significant increase ($p = 0.007$) in step-duration variability from $16\text{ms}$ (baseline) to $21\text{ms}$ (load). Our findings demonstrate that IMUs are a proved alternative to static setups that usually require a non-trivial infrastructure, e.g. optical movement tracking.

5.2 Introduction

Increasing age might affect people in motoric skills as well as in cognitive performance. In general, the ability to sit, stand, walk and to perform activities of daily living (ADL) can be condensed in the term "mobility". Mobility contributes the lion’s share to an elderly persons’ independence and as such is a combination of mental resources and their physical expressions. Limited motoric or mental capabilities result in a lowered mobility and with reduced mobility the risk of falling (RoF) increases [87]. If we can objectively measure mobility of a person, there might be a model to predict her RoF. This was our main motivation: To estimate automatically the mobility of elderly people with future applications for safety in mind (e.g. reducing RoF).

In this paper, we focus on gait features as they are by nature closely linked to RoF. It is known that gait features are affected by cognitive load levels of a subject. Especially for elderly people the threshold level
where gait-feature-changes are noticeable is low \[86\] (compared to younger individuals’ levels), sometimes as low as a task of subtracting numbers.

We demonstrate that a sensor-based automatic acquisition and analysis setup is an efficient alternative to the currently used methods. To this purpose we looked at the step duration and its dynamics in situations with and without cognitive load. We present the analysis and results of a study with elderly people (aged 65+) and analyze the changes of gait features between a baseline setting (i.e. common walk) and a setting where the subjects were under elevated cognitive load while walking. We compare state-of-the-art (SoA) to our approach and show that we can detect the differences between situations with elevated cognitive load and situations without.

Furthermore, our longer-term goal is it to contribute to a transparent estimation system - not requiring any special action by the subjects - to make statements about a human’s relative mental load level and the consequences for her motoric performance. We position our work as an initial contribution to that goal.

5.3 Related Work

5.3.1 Tests not using electronic devices

In general, in geriatrics the term mobility refers to a person’s aptitude of performing a physical task in her everyday life. The definition of mobility is usually tailored to a specific target group, e.g. hospitalized patients or subjects at home and to a specific environment, e.g. medical care facility, home etc. \[115, 116\].

One of the most often used mobility indices (MI) is the "timed-up-and-go" test (TUG) first introduced by Podsialdo et al. \[23\] which is analyzed in more detail by Thrane et al. in \[24\]. TUG is often used as an indicator for RoF of a person. It measures the time a person needs to rise from a chair and walk a given distance. The "Short Physical Performance Battery" (SPPB) \[117\] focuses on the lower extremities and their functionality. SPPB can be divided into three sections: Balance Tests, Gait Speed Test and Chair Stand Tests (similar to TUG). The "Motor Assessment Scale" (MAS) \[118\] analyzes 8 motor functions. In particular, it also assesses transition movements (standing up), static tasks (standing still) and dynamic tasks (walking).
5.3.2 Tests with electronic devices

Webster et al. [102] introduced the GAITRite sensor system used for the evaluation of walking performance\(^1\). This sensor system consists of a pressure sensitive mat in various sizes. The largest model is about 1\(m\) wide and 7.5\(m\) long, allowing for the analysis of step length, step width and frequency. Webster et al. compared the system’s performance to a state-of-the-art optical 3D motion tracking system, e.g. Vicon. Van Iersel et al. [119] investigated the effect of cognitive dual tasking on balance of older adults. They used the GaitRite system for data acquisition and extracted spatial features of gait (e.g. stride length) and temporal gait features (time variability). Hollman et al. [120] performed a study incorporating older and younger subjects. In that study they analyzed the differences of dual-task walking between the two age groups. Kuys et al. [35] used a system to evaluate spatio-temporal gait features of stroke patients: the researchers used the data from the system to compute the MAS gait score of the patients. Bamberg et al. [32] present a sensor system that provides three pressure measuring points as well as orientation data of the feet using intertial measurement units (IMU). All system components were integrated in a shoe. The authors used that system to analyze heel-strike and toe-off events during gait periods as well as the feet orientation. Within a sport-focused setting Strohrmann et al. [121] used IMUs attached to the legs to analyze the running behavior of healthy younger people.

5.3.3 Evaluating cognitive features

Theill et al. [122] suggest that performing simple mathematical calculations\(^2\) suffices to generate sufficient cognitive load to induce a measurable physical response of a subject. In their paper, they present a precise method for measuring situations with cognitive loads of varying degree. Schaefer et al. [123] demonstrate that elderly subjects, when put under cognitive load, express an increased variance in step frequency and might even show difficulties maintaining balance. They used a variant of the N-Back test [124] to induce elevated cognitive load levels in their subjects. Schaefer et al. contributed to our motivation of evaluation training impact on cognitive performance and motoric fitness.

---

\(^1\) GaitRite Gold, CIR Systems, Easton, PA.
\(^2\) e.g. starting from 50 subtract consecutively 2.
Cinaz et al. developed in [125] a system to estimate mental workload using the heart rate variability. They were able to train a classifier separating the instances of low mental workload from samples with higher mental workload. Cinaz et al. showed that the links between cognitive load and physical expression are abundant and feasible to measure.

5.4 Experiment

5.4.1 Hypotheses and Approach

We aimed at demonstrating the feasibility of using sensor data from IMUs to automatically detect periods of regular walk. During those intervals, we distinguished between situations without and situations with cognitive load. For this purpose we have setup a study where elderly people were asked to perform a simple walking task once with, and once without a cognitive task in parallel. In the following sections we are going to provide the details.

5.4.2 Participants

Elderly people at the age 65 or older were recruited for the study. The inclusion criteria for participants was an age within the range \([65, 85] \). The applicants for participation had to pass a cognitive screening test [88] in order to be included in the study. To assess their overall motor activity we performed TUG. We were interested in healthy subjects with no evident disabilities. Subjects included in our study tested normal in the cognitive test and in the motoric evaluation, TUG. Out of 63 participants 48 individuals (32 female and 16 male) successfully completed the study and we could use their data for our evaluation\(^3\). The subjects’ demographics are listed in table 5.1.

5.4.3 Measurement Setup

For the testings we equipped the subjects with sensor devices. In order to track gait features of our subjects we used four IMUs by XSens [126]. With Velcro straps we attached on each shin and each thigh a sensor having the x-axis pointing towards ground (cf. fig. 5.1). Four

\(^3\)For the first 15 subjects our measurement setup suffered a technical problem and the recordings failed. One subject did not perform a testing at all. Our set therefore contains data from 47 subjects.
Table 5.1: Age distribution of the 48 subjects.

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>overall</td>
<td>65</td>
<td>84</td>
<td>71.77</td>
<td>4.89</td>
</tr>
<tr>
<td>female</td>
<td>65</td>
<td>81</td>
<td>71.71</td>
<td>4.70</td>
</tr>
<tr>
<td>male</td>
<td>65</td>
<td>84</td>
<td>71.88</td>
<td>5.33</td>
</tr>
</tbody>
</table>

Figure 5.1: Subject with four sensors and one gateway device.

Sensors at these locations allowed us to track more features than just step durations: angles between shin and thigh, leg orientation etc. The devices were tethered; the data was sent to and power comes from a gateway device (transmit station) that was worn with a belt around the subjects' waist. We configured the devices to report raw acceleration, rotation rate values, but also Euler angles which reflect the orientation in space relative to the earth.

At 50Hz motion data was streamed via Bluetooth to a notebook where we stored it for later analysis. A higher sampling rate was not possible due to bandwidth limitation of the Bluetooth system.

The subjects were additionally recorded on video for a validity check of our automatic feature calculations. Data analysis was performed offline using MATLAB.
5.4.4 Test Procedure

At the beginning of the test session the mental test [88] (Mini Mental State Evaluation, MMSE) was presented to the subjects in direct interaction with an expert. This study controller (a psychologist) asked the questions and noted the answers of the subjects on the evaluation sheets. We required the subjects to score above 26 to be included in our study.

Motoric testing was performed with an instance of TUG: subjects were asked to sit on a regular chair. The controller then asked the subjects to stand up. Time until completion was measured starting from the issue of the command until the subject was in an upright position. TUG scores above 10 seconds are considered as noticeable [117].

During testings, subjects were two times required to walk down a aisle of length 10m, turn around and walk back again (baseline testing, task 1). In the second part of the testing we asked them to do the walk as before but now while subtracting from a random number provided by us (arbitrarily chosen from the set [501, 502, 503]) at each step a specific number, i.e. 7 (task 2).

5.5 Methods

We primarily wanted to compare statistics of the data from the baseline task to data from the cognitive-load task. To this purpose, we firstly detected the intervals in our data that were of interest, e.g. periods of straight walking, segmented by turning points. These intervals were

Figure 5.2: The path for tasks 1 and 2: subjects walked twice the distance of 10m.
detectable using the magnetometer data. In \textbf{fig. 5.3a}, an axis of a magnetometer is plotted in blue. In the high frequency spectrum, the steps are visible, the four changes of the mean value correlate with the walking direction of the subject. We calculated the turning points by first applying low-pass filter to the data (red curve). Then, we used the sign of the slope (magenta) of this curve as the limits for the intervals. Finally, we declared the turning point as the mid-point of a decreasing interval. To maintain comparability to related work we analyzed the walking interval for the first $20m$, $(2 \times 10m)$. Therefore, only data until the second turning point (start position) was used. The turning points were detected by our algorithm without false positives. At each turning point we disregarded two steps before and one step afterward since we were only interested in statistics from straight walk.

Next we detected the steps using state-of-the-art \cite{121} on the accelerometer signals. The steps manifest themselves as peaks in the accelerometer signal. In \textbf{fig. 5.3b} a fragment of a data set is shown: the accelerometer signal is in blue, the step locations are marked with red circles.
5.5. Methods

(a) Interval detection (x-axis). The magnetometer data (blue) is smoothed (red). The inflection points of the smoothed data mark the turning points.

(b) Step detection on accelerometer data (sampled at 128 Hz). Steps are detected with a peak detection algorithm in MATLAB.

Figure 5.3: Analyzing gait data. Turning-point detection (left) on the magnetometer data (sampled at 128 Hz); step detection (right) on the accelerometer data.
Our focus lied on the variances of step duration for task 1 and task 2. Hence, the time delays between individual steps served as input for our further analysis. For each subject we calculated the step durations for the baseline task (task 1) and for the cognitively loaded task (task 2) in milliseconds. Next, we calculated for each task \( t = \{1, 2\} \) for each subject \( i \) the mean \( \mu^t_i \), the median \( m^t_i \) and standard deviation \( \sigma^t_i \) (or variance, resp.) of the step durations. We denote the collection of all \( \mu^t_k \) of all subjects for task \( k \) as the vector \( \bar{\mu}_k \). The definitions for \( \bar{\sigma}_k \) and \( \bar{m}_k \) are analogous. Since we are interested in individual changes we calculated the difference of \( \mu^t_i \) and \( \sigma^t_i \) between the two tasks for each subject \( i \): \( \tilde{\mu}^t_i : = \mu^t_2 - \mu^t_1 \), \( \tilde{\sigma}^t_i : = \sigma^t_2 - \sigma^t_1 \). So, \( \tilde{\mu}^3 \) is the positive or negative change of the mean value of the step durations for subject 3.

In our analysis we looked at the set of means for both tasks, \( \bar{\mu}_1 \), and \( \bar{\mu}_2 \), resp. We also considered the sets of standard deviation for both tasks, \( \bar{\sigma}_1 \) and \( \bar{\sigma}_2 \). Finally, we also analyzed the set of individual progresses, \( \bar{\tilde{\mu}} \) and \( \bar{\tilde{\sigma}} \).

In order to make a statement about the development of gait features between task 1 and task 2 we needed to compare the variances of step duration of the first task to those variances from the second task. A requirement for a valid comparison is the two sets originate from the same distribution, e.g. a Normal distribution. The distribution parameters for each of the sets might be different.

We used the Lilliefors test \([127]\) based on the Kolmogorov-Smirnov test \([128]\) to verify task-1 data and task-2 data are from the same distribution family. Lilliefors’ test performs better for smaller sample sizes than the Kolmogorov-Smirnov test.

For visualization, the QQ-Plot \([129]\) allows for graphical comparison of two distributions: it draws the quantiles of two empirical distributions against each other.

Finally, the variances of the two data sets were analyzed with repeated analysis of variance (ANOVA, \( \alpha = 0.05 \)).

### 5.6 Results

The validation of equality of distribution between the two sets yielded a positive result: in [fig. 5.4a](#) we show that the baseline data set and the cognitive load set originate from the same distribution family. The blue points represent the quantiles of the distributions. The absissa
represents the distribution for task 1 the ordinate is for task 2. Indicated in red is the linear interpolation line for the two sets. As can be seen the two sets relate in a linear manner to each other.

The evaluation of the Lilliefors test [127] for either set accepted the null hypothesis of the data originating from a normally distributed population with a confidence level $\alpha = 0.05$. 
Chapter 5: Dual-Tasks in Elderly People

Figure 5.4: Analyzing the effects of dual-task exposure on gait frequency variations.

(a) QQ-Plot of mean values for baseline task and cognitive load task. The linear spread suggests two normally distributed samples.

(b) Cumulative probability plot of the mean step-frequency variance for baseline task (blue) and cognitive load (green).

Figure 5.4: Analyzing the effects of dual-task exposure on gait frequency variations.
5.6. Results

During evaluation we noticed that the sensor at the shin positions produced the best signal-to-noise (SNR) ratio. The shin sensors were less susceptible to "motion noise" that may be introduced by low-friction clothing (like synthetic trousers) and the sensor devices moving uncontrolled relatively to the leg or textile. We believe this result is caused by a looser attachment of the thigh sensors as a consequence of the thigh being by nature more sensitive to pressure than the shin. A tight Velcro was considered uncomfortable at that position. Too tight strappings might even have had an impact on the gait pattern. The shin, however, is not that sensitive and the muscular tissue does not perform large movements. Due to this reasons we decided to evaluate for each subject data solely from one (e.g. the left) shin sensor. A manual verification of the peak positions proved that the step detection algorithm worked with 100% accuracy.

Cognitive load had a significant impact on the gait features. This effect on the variance of step duration can be seen in Figure 5.4b where we draw probability plots for the two sets. In the plot data points (e.g. step durations) are plotted against their probability. The blue points mark the data points from the first task, the data of the second task is in green.

We performed a person-independent ANOVA test: In Table 5.2a we list the results of our analysis. In each line we report the mean value for the features $\bar{\mu}_k$, $\bar{\sigma}_k$ and the median, $m_k$ resp., introduced in Section 5.5. Additional to the mean values of the features we provide also the standard deviation. All values are in milliseconds. The $p$-values in the last column in Table 5.2a indicate that all three features differ significantly between the two testings.
Table 5.2: Results of analysis

(a) ANOVA

<table>
<thead>
<tr>
<th>Feature</th>
<th>Task 1 (ms)</th>
<th>Task 2 (ms)</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{d}_k$</td>
<td>16.84 ± 5.17</td>
<td>21.64 ± 10.62</td>
<td>6.62</td>
<td>0.007</td>
</tr>
<tr>
<td>$\bar{m}_k$</td>
<td>513.04 ± 45.41</td>
<td>547.39 ± 63.82</td>
<td>8.85</td>
<td>0.0038</td>
</tr>
<tr>
<td>$\bar{\mu}_k$</td>
<td>514.93 ± 44.24</td>
<td>549.01 ± 62.88</td>
<td>9.04</td>
<td>0.0034</td>
</tr>
</tbody>
</table>

(b) Mean changes.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\delta}$</td>
<td>4.8065</td>
</tr>
<tr>
<td>$\bar{\mu}$</td>
<td>34.0807</td>
</tr>
</tbody>
</table>

Table 5.2b depicts the mean changes on gait features induced by the cognitive task. The standard deviation between the baseline task (task 1) and the cognitive load task has increased by 4.8 ms (mean). The mean of the mean values increased by 34.1 ms. The variability of the step duration changes from baseline to cognitive loaded situations and the mean step duration increases. Our findings are comparable to previous findings of related work [120, 119].

5.7 Conclusion and Future Work

In this paper we have taken the first step towards an autonomous mobility assessment system by automatically analyzing the correlations of gait features and cognitive load with an IMU setup. We have shown that by using step duration it is possible to distinguish between situations of cognitive load and those without. We have also provided a proof-of-concept for the feasibility of performing the analysis automatically. In our paper we successfully demonstrated that with a minimal setup of one single inertial measurement sensor it is feasible to conduct studies equivalent to SoA, but requiring substantially less infrastructure, e.g. no cameras, no human resources etc. at arbitrary locations.

We are going to base our future work on the results and findings of this study. We further believe that for future gait analysis it is pos-
possible to reduce the hardware requirements even more. We envision a single-sensor setup - untethered - providing us with gait features like the ones used here but also with additional ones. We believe that there are training effects over longer periods of time: redoing task 2 several times over a longer time span might reduce the effect of the cognitive load. We want to measure this progression in the future. Also, generalizing our setup even more in order to allow for many more movement features is planned for the future.

We envision an automatic system to assess mobility: an unobtrusive self-contained sensor system that constantly monitors the movement of its wearer. This paper represents a part of the whole, but for the future we want to add additional modalities and more importantly at some point leave the lab setting and go into real life environments.
In this chapter, we present a study using PIMU in physiotherapy patients and healthy subjects. We compare PIMU with state-of-the-art. Further, we show that PIMU is capable to support a physio therapist in his diagnoses by delivering objective data for tests that are often difficult to assess consistently even for experts with long-term experience.

This chapter was published in the Proceedings of the 8th International Conference on Body Area Networks titled Unobtrusive Assessment of Bipedal Balance Performance [68].
6.1 Abstract

Reduced postural stability are symptoms of many medical conditions. Depending on the conditions, there are training or medication strategies to ameliorate the balance of a subject. After medical treatment (surgery etc.) or in the context of an intervention/recovery strategy, affected patients are often assessed in functional gait assessments (FGA). An expert, e.g. a physio therapist (PT), can decide based on the outcome of such an assessment on future treatment plans. FGAs are often performed without technological assistance: a subject performs pre-defined tasks and the performance is evaluated visually by an expert. Existing technological assessment tools are scarcely used due to time and monetary restrictions. In this paper, we present a wearable sensor system that can be used for FGAs. Our system comprises a pressure-sensing component and inertial sensors to assess features known to correlate with balance. We validated our system against technological state of the art. We used the system on 6 patients and 5 healthy subjects. The system can distinguish between normal stance and stance with reduced postural control with an accuracy of more than 93%. Walking episodes were classified into two categories ("stable", "unstable") with 91%. Based on features of stance and features of gait, our system could discriminate between the group of healthy subjects and the group with reduced postural stability with an accuracy of 94%.

6.2 Introduction

There is a large number of possible illnesses and conditions that have an impact on features of gait and on the balance performance of a subject. Everyday causes like sleep deprivation might be sufficient to affect the balance of a person [130]. However, conditions like damages to the vestibular system (located in the inner ear), strength deficits in limb or core muscles, visual impairment etc. can manifest in difficulties maintaining a balanced posture. Even though some patients show improved stability in a dynamic situation, i.e. walking, they would move even more stable without any balance impairments. It is safe to state that balance difficulties are reflected in static and dynamic situations. Hence, if one could assess features of balance in a static state and features of gait in a dynamic case one would be equipped with mea-
sures to get a notion on the overall balance performance of a subject. Here, we refer to this as "bipedal performance" and it comprises stance stability and gait stability.

The stability of a walking person can be estimated by measuring the variance of step frequency [67]. Measuring directly a subject's balance is more involving as it translates into the task of continuously estimating a subject's center of mass (COM). As long as the projection of the COM onto the ground plane falls into the convex polygon spanned by a subject's feet, a "balanced posture" is assumed [131]. Continuously estimating the COM would require accurate measurements of a subject's physical properties and a way of tracking her body-dynamics. Previous work achieves this by using optical motion capture or a multitude of inertial measurement units (IMU) attached to various parts of the body. Related work has shown, though, that there exists a correlation between the dynamics of the center of pressure (COP) beneath a subject's feet and the quality of her balance [132].

In clinical settings, e.g. for functional gait analyses (FGA) most of the assessments are performed manually, by the interpretation of a well-trained expert. This expert could be a physio therapist (PT) or a medial doctor. FGAs are usually multi-item physical tasks that need to be performed by a patient. The PT would then characterize or rate a patient's performance for each item. However, this rating is difficult and often ambiguous. Other assessments also include feedback from the patients. Due to limited resources both in time and space, technological support is only sought rarely. Systems like GaitRite [102] or Zebris [80] require to be pre-installed in a room and require multiple experts to be operated.

Common practices to assess bipedal performance can be clustered into three classes: "immobile systems" installed in a dedicated facility, "mobile" or "wearable systems" that require a multitude of sensors on a subject and "technology rare" approaches relying on expert knowledge and possibly on subject feedback. For clinical assessments, a combination of all three classes is desired: the ease of use of an pen-and-paper assessment combined with the comprehensive assessment of a wearable system topped by the robustness of a pre-installed system.

We are not going to present the silver bullet, but we think that our solution facilitates objective assessments of bipedal performance. We built a high-resolution pressure sensor system combined with an inertial measurement unit (IMU). We presented the technical features of
our system earlier in [65]. We will show in this paper that the combination of a pressure insole with an IMU enables us to assess bipedal performance in dynamic and static situations. Our system is unobtrusive and allows for continuous assessment of static balance and dynamic gait stability. Additionally, it comprises a display device, e.g. a smart phone, that not only acts as a controlling device, but also gathers data from a subject’s shoe sensors and calculates balance features. Each foot sensor tracks the center-of-pressure and sends the coordinates to a smart phone. On a mobile device, an algorithm calculates a surrogate for bio-mechanical stability estimation: a Stabilogram Diffusion Analysis, SDA, is calculated in real-time. As will be motivated later, this calculation provides reliable estimates on a subjects balance. Raw sensor data and features can be stored on the sensor devices for later analysis. On the smart phone, real-time information can be presented to a user (PT, medical doctor).

We evaluated the performance of our system and show that it matches the requirements on an assessment tool that might support PTs or medial doctors for evaluations of bipedal performances. We compared our system to state-of-the-art (SotA), i.e. the ZEBRIS system [80], to validate the sensory and algorithmic system performance. To show applicability and classification performance of our system, we tested 5 healthy subjects and 6 patients. We attended various FGAs and asked the patients if they would wear our system during the tests. A selected set of these test items were then performed by the group of healthy subjects. We show that our system is capable of detecting episodes of reduced bipedal performance with an accuracy of above 91%. Our system continuously calculates features known to correlate with balance performance [133, 132] by utilizing the dynamics of the center of pressure, COP. During standing, episodes of limited balance are detected more than 93% correctly. Our system can further distinguish between healthy subjects and patients with an accuracy above 94%.

6.3 Related Work

Gait Analysis refers to research that focuses on features of gait. In [32] Bamberg et al. present a sensor system that provides three pressure measuring points as well as orientation data of the feet using inertial measurement units (IMU). All system components were integrated in
a shoe. The authors use that system to analyze heel-strike and toe-off events during gait periods as well as the feet orientation. Kuys et al. [35] use the GAITRite system [81] to evaluate spatio-temporal gait features of stroke patients. Adelsberger et al. [67] rely on IMUs attached to the subjects’ legs to detect situations of higher cognitive load and a thereby induced reduction of gait stability.

**Balance Assessments** are non-trivial. Various authors (e.g. [134, 135]), tackle this problem by estimating a subject's center of mass (COM) which requires exact tracking of body posture and possibly calibration of physical properties of a subject (weight etc.). An optical or inertial motion capture (MoCap) system can then use this calibration data to track the movement of the subject’s limbs and trunk. However, the setup of an accurate COM-estimation system that meets these accuracy requirements can be time consuming since multiple markers are required per limb (see Vicon manual) or multiple sensor nodes need to be attached to the body.

Other work analyzes the relationship between COM and center of pressure (COP) beneath a subject’s feet, cf. [133, 136, 137]. Tanaka et al. [132] decoupled the problem of balance estimation from COM estimation. In their work, look at statistics of COP motion. Inspired by Einstein's theory on Brownian Motion [138], they model the motion of COP similarly, by a stabilogram diffusion analysis (SDA) [133]. Their findings show that parameters of the Brownian motion model applied to COP position correlate well with postural stability/instability. Tanaka et al. [132] show that for an SDA, short term diffusion coefficients, $D_S$, are a good indicator of balance performance of a subject. Specifically, people with balance problems show significantly higher values for $D_S$ than normal subjects. Also, mean square displacements are significantly larger in the group with balance issues than they are in the normal group.

### 6.4 System Description

Our sensor system comprises for each foot a size adjustable pressure insole with 1260 force sensing resistors (FSR), a sensor board that samples every FSR, and an inertial measurement unit (IMU) with a communication (ANT+) and a storage (MicroSD card) module. The insole is manufactured by TekScan and we modified it to be applicable in our system. The pressure-sensitive elements cover an area of $25\text{mm}^2$. 
The insole can be adapted and integrated into virtually any shoe of a large size range, e.g. from children size 13 up to male size 12.5. Since it is very thin (< 0.5mm) it is not noticed if installed below a regular shoe-insole. A remote device (e.g. Smart Phone) works as a controller to the shoe sensors. It also takes the role of a notification and display device. [Fig. 6.1] shows the shoe-integrated parts of the system. A more detailed description of the hardware and system capabilities can be read in [65]. For each foot, the system calculates in real-time the center of pressure (COP), i.e. the coordinates of the center of the ground-reacting forces.

For a well balanced, static posture weight would be evenly distributed onto both feet. For such (artificial) postures only the forward/backward movement of the COP needed to be estimated. However, in general, weight is not shared evenly between the feet due to different reasons. Thus, to calculate an estimate for a global COP of a human posture, $\text{COP}_G$, the estimates of both feet need to be combined:

$$\text{COP}_G = w_l \cdot \text{COP}_L + w_r \cdot \text{COP}_R.$$ 

Weights $w_L$ and $w_R$ reflect the lateral weight distribution,

$$w_{[L,R]} = W_{[L,R]}/(W_L + W_R),$$

where $W_{[R,L]}$ represents the estimated weight on the right/left sole. See the right part in [Fig. 6.1] for a sample $\text{COP}_R$.

![Figure 6.1](image)

**Figure 6.1:** The Sensor system is shown on the left; on the right, a sample data frame with COP estimation is shown.
At run-time, \( \text{COP}_{[R,L]} \) are calculated and forwarded to the smartphone where \( \text{COP}_G \) is calculated. Our system is not able to track the distances between the feet due to lack of specific hardware (distance measurement). As a consequence, it cannot conclusively detect every state of the COP-coordinates that indicate an unstable posture. However, the combination of the pressures exerted on each foot as a weight factor for the calculation of \( \text{COP}_G \) resulted in an accurate classification.

At start-up, the smartphone accumulates for 5 seconds the COP estimates before it starts estimating the parameters for the SDA. The initial idea behind SDA was motivated by analyzing Brownian Motion in liquids. From [138] it is known that the squared mean displacement, \( \langle \Delta y_p^2 \rangle \), of a Brownian particle for a given time resolution, \( \Delta t \), is proportional to \( \Delta t \) times a diffusion coefficient \( D \), i.e. \( \langle \Delta y_p^2 \rangle = 2D\Delta t \). The diffusion coefficient \( D \) is an average measure of the stochastic activity of a random walker and \( y_p \) is its displacement in space. In our work, \( y_p \) is the displacement of \( \text{COP}_G \) over time. Collins et. al [133] provide a probably more intuitive definition:

\[
\langle \Delta y_p^2 \rangle_{\Delta t} = \frac{\sum_{i=1}^{N-m} (\Delta_i y_p)^2}{(N - m)} (6.2)
\]

with given \( \Delta t \) spanning \( m \) data points from a total of \( N \) data points. The variable \( \Delta t \) ranged from 0.05s to 3.0s in our analysis, since longer time intervals do not provide additional information ([136]) and also to promote a faster feature assessment due to shorter acquisition time. The squared mean displacement, \( \langle \Delta y_p^2 \rangle \), depends non-linearly on \( \Delta t \), however it can be separated into two linear parts, one for small \( \Delta t \) (\( I_s := [0s, 1.0s] \)) and one for longer \( \Delta t \) (\( I_L := (1.0s, 3.0s] \)). Both parts can be approximated by a linear model

\[
\langle \Delta y_p^2 \rangle_{[I_s,I_L]} = \gamma_0 + \gamma_1 \Delta t, (6.3)
\]

however the model parameters differ significantly between the short-term interval and the longer-term interval. Consequently, the diffusion coefficients differ between the two time intervals. We define the diffusion coefficient for short-term intervals as \( D_s \) and the coefficient for longer-term intervals is dubbed \( D_L \), resp. For each time interval,
the diffusion coefficients $D_S$ and $D_L$ were found by fitting the data to a linear model with a least squares approach.

Concurrently to pressure data processing, the system acquired step timings. The variance of step frequency was calculated for the steps within a 5-seconds time window. Episodes of standing were detected using a combination of accelerometer data and pressure data.

### 6.5 System Validation

The ZEBRIS system comprises a treadmill with pressure sensitive points below the walking area of size $(150cm \times 50cm)$. Every sensitive point covers an area of approximately $150mm^2$. The pressure data is sampled at $100Hz$ and forwarded to a PC where the analysis is performed. It is not published how the ZEBRIS system calculates COP coordinates. We assumed that it is similar to other related work \cite{139}. We compared the COP coordinates of the ZEBRIS system with our results. Due to the fact that our sensor coordinate system is fixed to a subject, while with ZEBRIS a subject moves relatively to the coordinate system, a comparison of COP coordinates during gait would be error-prone. Hence, we recorded a subject standing on the treadmill wearing our system. Multiple features were compared: RMS-error of normalized COP coordinates and normalized coordinate variance. Coordinates were normalized to the bounding box of a foot. We also wanted to compare the sensor components of both systems, so we additionally used our own algorithms to calculate the COP and applied them to the raw data of the ZEBRIS system.

### 6.6 Classification

We attended FGAs of 6 patients. They were evaluated by a PT using a standardized 10-item test that contains items based on related work \cite{140, 115}. For each item except number 10 the subjects needed to walk 20m. The table below lists the various items.

Additionally, we asked the subjects to stand for 20 seconds with eyes open (item 11) and for 20 seconds with eyes closed (item 12). By closing the eyes, support from the visual system is removed and a subject is forced to rely on the vestibular system \cite{141} and to some extend on the tactile feedback from the feet. We asked the healthy subjects to perform the items, 1,3,4,7,8,11,12. The other items did not
challenge the balance of healthy subjects and all 6 patients but one did not show any special reactions. We video taped the sessions for labeling and verification.

We extracted for each of the test items multiple features of \( \text{COP}_G \), e.g. range, variance, standard deviation and for dynamic items also step-frequency variance. For the static items 11 and 12 we additionally calculated the SDA diffusion parameters \( D_S \) and \( D_L \) (using equation 6.2) and mean displacements. \( D_S \) was calculated within \( \Delta t \in [0s, 1.0s] \) and \( D_L \) was based on \( \Delta t \in (1.0s, 3s] \) (cf. [140, 115]). Using the video footage, we labeled episodes of reduced bipedal performance and episodes of normal performance. We trained two-class SVMs to

- differentiate between episodes of normal and episodes of reduced bipedal performance,
- differentiate between healthy subjects and subjects with balance defects.

The features presented to the SVM were the moving averages of the above features within a 0.5 s window. The SVMs were trained on 80% of the samples from all subjects and their performances were evaluated on the remaining 20%. For a more accurate classifier performance assessment, we iterated this learning-testing procedure for 100 cycles, every time another random subset was assigned to the learning set.

### 6.7 Results

For the evaluation we normalized the coordinates to make them comparable. This was necessary, because the sensitive area of our system comprised \((21 \times 60)\) points for each foot, while the ZEBRIS system worked with one large sensing area. We calculated a bounding box for each foot for every ZEBRIS data frame. Since the dimensions
of the bounding box might change, we normalized the COP coordinates for our system and the ZEBRIS system, i.e. we mapped them to \(([0, 1] \times [0, 1])\). In a first step, we compared the COP coordinates reported by the ZEBRIS system (black box) to our coordinates. Table 6.2 (red) shows the results.

<table>
<thead>
<tr>
<th>Dim</th>
<th>RMS-Error (mm)</th>
<th>var(Error) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>5.33</td>
<td>2.82</td>
</tr>
<tr>
<td>y</td>
<td>5.28</td>
<td>3.13</td>
</tr>
<tr>
<td>x</td>
<td>1.34</td>
<td>1.21</td>
</tr>
<tr>
<td>y</td>
<td>1.88</td>
<td>1.73</td>
</tr>
</tbody>
</table>

Table 6.2: ZEBRIS COP-proprietary coordinates vs. our COP-coordinates (red), ZEBRIS-data driven COP vs. our COP-coordinates (green). All sizes in mm.

Unfortunately, the ZEBRIS system reported discrete values for the COP coordinates. This fact had to be considered while evaluating the results since one sensitive element was 6 times larger than one sensor point in our system. To compare the sensing hardware, we applied our own algorithms to calculate the COP for the ZEBRIS system. This way, we could remove the uncertainty due to the black-box nature of the ZEBRIS data. Table 6.2 (green) shows the results. We acquired data from 5 healthy subjects (m:4, f:1) and 6 patients (m:2, f:4). The healthy subjects’ ages ranged from 21–34 years, \((\mu = 28, \sigma = 4.74)\). The patients’ ages ranged from 19 – 65 years, \((\mu = 45, \sigma = 15.7)\). Healthy subjects followed a physically active lifestyle; the tests were performed in a gym. Their foot sizes ranged from 39 to 46 \((\mu = 42.6, \sigma = 2.60)\). The patients were mentally healthy, but had balance defects due to several causes. Classification between healthy subjects and patients for the dynamic items (1,3,4,7,8) was based on statistical features calculated on \(COP_G (\sigma, \text{range})\) and step frequency \((\mu, \sigma)\) within a 0.5 second window. On the items, 11, and 12 we performed an SDA to evaluate the subjects’ balance stability and calculated \(D_S, D_L\) and \(\mu(\Delta y^2_p)\). The SDA on \(COP_G\)-time series was performed for time slots ranging from 50ms to 3000ms, see Table 6.3. On average, the range of COP coordinates was about 40% larger for patients than for healthy subjects, i.e. the instability was measurable. The SVM we trained for detecting unstable situations showed an accuracy of 93.32% on items 11 and 12. On items 1,3,4,7,8 the achieved classification accuracy was 91.28%. Bipedal performance of was assigned correctly to the specific subject group with an accuracy of 94%.
6.8. Conclusion and Outlook

We presented an unobtrusive system for automatic and continuous assessment of bipedal performance. A sensor insole connected to an acquisition system for pressure and inertial data calculated immediate features like center of pressure and step frequency. These features were submitted to a smart phone that aggregated the data, calculated higher-level features (SDA) and performed classification. We trained SVMs to classify between episodes of reduced bipedal performance (dynamic and static) and stable situations. Further, we trained SVMs to differentiate between healthy subjects and patients. The episode classification task could be performed with an accuracy higher than 91%, the subject classification worked correctly 94% of the times.

We showed successfully that we can estimate SDA features known to correlate with the bipedal performance of a subject. Further, we showed that our system could provide valuable data to PT or medical doctors in their assessment tasks.

Our research focus lies on movement analysis, mainly targeted to the elderly population. We envision a system that unobtrusively and continuously tracks multiple features of gait and is able to detect trends of gait and stability performance. We believe that we added a major step into the direction of such a system.

<table>
<thead>
<tr>
<th></th>
<th>( \mu (D_S) )</th>
<th>( \sigma (D_S) )</th>
<th>( \mu (\langle \Delta y_p^2 \rangle) ) (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_{11} )</td>
<td>8.17</td>
<td>3.12</td>
<td>20.18</td>
</tr>
<tr>
<td>( P_{11} )</td>
<td>15.83</td>
<td>7.44</td>
<td>31.92</td>
</tr>
<tr>
<td>( H_{12} )</td>
<td>16.39</td>
<td>8.01</td>
<td>30.24</td>
</tr>
<tr>
<td>( P_{12} )</td>
<td>20.18</td>
<td>9.87</td>
<td>49.11</td>
</tr>
</tbody>
</table>

*Table 6.3: COP features for healthy subjects (H) and patients (P).*
This chapter presents a study in patients with benign paroxysmal positional vertigo (BPPV). We compared the reactions of patients and of a healthy control group to a standard therapy for BPPV.

This chapter was published in the IEEE Transactions on Biomedical Engineering, 2014 titled Automated romberg testing in patients with benign paroxysmal positional vertigo and healthy subjects [69].
7.1 Abstract

**Objective:** Benign paroxysmal positional vertigo (BPPV) is the most common cause of dizziness. The underlying pathomechanism responsible for the recurrent vertigo attacks has been elucidated in detail, and highly effective treatment strategies (liberation maneuvers) have been developed. However, many BPPV patients complain about problems of balance especially following liberation maneuvers.

**Aim:** To objectively demonstrate differences in balance performance in BPPV patients compared to healthy subjects both prior and after BPPV liberation maneuvers.

**Methods:** Seven patients with BPPV of the posterior semicircular canal and 9 healthy subjects participated. To assess balance while standing, we analyzed the location and temporal stability of the center of pressure recorded by pressure-sensitive electronic soles during Romberg testing (on stable ground and on foam) and tandem stand. To assess regularity of gait, we analyzed the step frequency during walking of 50m. All tests were performed prior and after liberation maneuvers in both groups.

**Results:** Healthy subjects and patients differ significantly in their balance performance and use different stabilization strategies both prior and after liberation maneuvers. Both Romberg tests indicated poorer balance in BPPV patients (mean COP shifted towards toes), especially in the post-treatment tests, while tandem stand appeared unaltered. We did not observe differences in escorted (by an experimenter) walking regularities between patients and healthy subjects and between pre- and post-maneuver testing.

**Conclusion and significance:** Our findings confirm the typical clinical observation of a further post-treatment deterioration of already impaired postural performance in BPPV patients. While the etiology and the time course of this peculiar problem warrants further studies, the treating physician should be familiar with this transient side effect of therapeutic maneuvers to provide adequate counseling of patients. Finally, we successfully demonstrated the pressure-sensitive electronic soles as a new and potentially useful tool for both clinical and research purposes.
7.2 Introduction

The probability that a person experiences benign paroxysmal positional vertigo (BPPV) at least once during his lifetime is 2.4% [90]. BPPV is by far the most common neuro-otological disorder [142, 143, 144, 145, 146, 147]. Whilst the signs and symptoms of BPPV (vertigo, disorientation, autonomic disturbances) can be wearing, the prognosis is excellent: 80% – 90% of the patients do not show signs of BPPV after the first treatment, close to 100% are free of symptoms after the third. Often, BPPV also resolves spontaneously [148]. BPPV is caused by detached calcium carbonate crystals that float freely in the endolymph of the vestibular labyrinth. Normally, these crystals are attached to the otolithic membrane where they enable the sensing of linear acceleration including gravity. If, on the affected side the free-floating crystals happen to enter one or more of the three semicircular canals, this so-called canalolithiasis causes BPPV whenever patients re-orient their heads relative to gravity. Since the specific weight of the crystals exceeds the specific weight of the endolymph, the crystals always sediment to the lowest point of the affected semicircular canal, thereby causing a temporary deflection of its cupula. This effect, in turn, leads to a transient change of the firing rate in the respective vestibular neurons and consequently to nystagmus and vertigo [149]. Canalolithiasis, and therefore BPPV, is best diagnosed by the Hallpike maneuver (for the posterior semicircular canals) [150] or the supine roll maneuver (for the lateral semicircular canals) [151, 152]. The direction of the positional nystagmus elicited by these maneuvers (Hallpike: geotropic vertical-torsional positional nystagmus; supine roll: geotropic or apogeotropic horizontal positional nystagmus) allows determining which of the three semicircular canals is affected by canalolithiasis on either side. Apart from positional vertigo, patients often report various degrees of unsteadiness during standing and walking, which is probably due to the abnormal vestibular signals from the affected semicircular canals. Canalolithiasis is a benign condition, as it can be treated by so-called liberation maneuvers that have a very high success rate (up to 80 – 90% of a single maneuver [91]). Rarely, patients need repetitive maneuvers, which are usually performed at intervals of a few days [153]. The liberation maneuvers for the most common form of BPPV, i.e. the canalolithiasis of a posterior semicircular canal, are the Epley [154] (see fig. 7.3) and the Semont [155] maneuvers. After liberation maneuvers, despite their effectiveness, patients commonly experience
a transient unsteadiness [92]. This feeling of decreased stability while standing and walking may last hours, sometimes up to several days. To the best of our knowledge, it has never been assessed, whether this post-liberation-maneuver symptom reflects genuine imbalance. The aim of this study, therefore, was to objectively quantify postural balance immediately after liberation maneuvers and compare it to measurements performed before the maneuvers. We asked the following questions:

1. Are bipedal performances of BPPV patients significantly impaired as a result of canalolithiasis?

2. Do canalolith liberation maneuvers lead to measurable deteriorations of bipedal performances of BPPV patients? We hypothesized that in patients with BPPV, liberation maneuvers would move the crystals out of the affected canal back to the utricle where they would sediment upon the utricular macula and potentially disturb gravity perception and hence postural stability [92].

3. Do liberation maneuvers also lead to a transient deterioration of bipedal performances in healthy human subjects and, if present, are they different from those in BPPV patients?
We formulate these questions in three hypotheses:

**H1:** Bipedal performance in BPPV patients are statistically significantly different to performance in healthy subjects.

**H2:** Bipedal performance deteriorates in BPPV patients as a result to canalolith liberation maneuvers.

**H3:** Liberation maneuvers do not have a statistically significant effect on bipedal performance in healthy subjects.

Assessing bipedal performance, i.e. parameters of standing and walking, is not a trivial task. Studies so far used force sensitive platforms (by, e.g. Kistler, AMTI etc.), treadmills equipped with a force sensitive belt (e.g. Zebris), force sensitive surfaces (by, e.g. GaitRite) or optical motion tracking (e.g. Vicon). Generally, these systems provide good temporal and spatial resolution; a major drawback, however, is their stationary setup. These systems have a limited acquisition area (e.g. GaitRite, Vicon), need to be installed in a dedicated location (e.g. Vicon, Zebris), or require special gear worn by subjects (e.g. optical markers, Vicon). In contrast to an estimation performed by other systems, we used a self-developed system that directly measures the force applied to the subjects’ feet soles with more than 1200 pressure-sensitive points. For this study, the system was integrated in gymnastic shoes of different sizes. A smart phone was used as a remote controller via a wireless connection. Direct streaming to the smart-phone was possible, but the data were also stored on a local memory card for later download and offline computational analysis. The technology and analysis elaborated in this work can deliver the required information on the effects of treatments affecting bipedal performance.

### 7.3 Methods and Material

The Romberg test and its variants, which reflect postural control, are most commonly assessed by a medical expert who scores different aspects of the subject’s performance. While some parameters are measurable, e.g. time, others allow a qualitative appraisal only. Thus, the "degree of imbalance" is very difficult to assess by visual inspection and requires an experienced expert.

Several systems provide objective measures of different features of gait. The GaitRite system is a pressure sensitive carpet. Depending
on the model, the GaitRite system can be up to 10m long. Subjects are required to walk over the carpet and the system measures and calculates balance distribution, stance width, speed etc. The Zebris system consists of a treadmill with a pressure-sensitive surface. While this system is not limited in length, the locomotion in place influences the walking style of subjects [156].

7.3.1 Assessments

The study was approved by the local ethical review committee. All subjects were given a small brochure with relevant information on BPPV, the study procedure and sensor setup, possible risks, privacy and the freedom to withdraw from participating in the study at any time without consequences. If subjects agreed to participate, they were asked to sign the corresponding consent form.

7.3.2 Subjects

Testing was performed on the ward of the Interdisciplinary Center for Vertigo and Balance Disorders of University Hospital Zurich. Participants were selected consecutively from the group of scheduled outpatients seen by a neurologist, whenever the patients gave a typical history of BPPV due to canalolithiasis. If, in the course of the protocol, the patients did not show typical positional nystagmus following the provocation maneuvers at the bedside, they were excluded from the analysis. The data acquisition protocol did not interfere with diagnostic and therapeutic procedures and the clinical appointment was only slightly prolonged. Healthy control subjects were recruited among the co-workers of the authors. There was no positional nystagmus detected in any of the control subjects.

7.3.3 Tools

The recording system consisted of two parts: an inertial measurement unit (IMU) and a force-sensitive plastic foil with more than 1200 force-sensitive resistors (see fig. 7.2). The IMU recorded acceleration, rotation rates and magnetic field readings, each in 3 dimensions. The force data were structured in a 2-dimensional matrix: X-coordinates (1-20) represented the transversal dimension (inner side to outer side of the feet), Y-coordinates represented the longitudinal dimension (from heel
to toes). The system was compared in related work to state-of-the-art systems, e.g. the Zebris Rehawalk system (see [68]). A sensing element covered $5 \times 5 \text{mm}^2$, thus an increment of 1 in one dimension represented a physical shift of $5 \text{mm}$ in the same direction. The foil matched the shape of a foot and could be adapted with a pair of scissors, e.g., to match any shoe size. We prepared three different size pairs: EU sizes 37, 42 and 46. The sensor foils were then glued into gymnastic shoes using double-sided adhesive tape. Gymnastic shoes were preferred over the patients’ personal shoes due to their simplicity (no artificial heel rise or bendings on the sole) and the tight fitting to the feet.

During all tests, the system recorded inertial measurement unit (IMU) data of both feet, e.g. acceleration, rotation rates and magnetic field values at 128Hz. Concurrently, the sensors sampled the force distribution beneath the subjects’ feet. All data were stored on the SD cards of the sensors for off-line analysis.

The participants were asked to perform a set of four standardized tests, including variations of the Romberg test [157], before and after therapy that consisted of the liberation maneuver. Participants were first asked to stand still with their eyes closed and with their feet put side by side for 20 seconds (test $R_1$). The second test was similar: participants had to repeat task 1 while standing on a foam mat, as shown in fig. 7.7a ($R_2$). The third test consisted of tandem stance on the floor with eyes closed (T). Finally, all participants were asked to walk straight 50 meters at their personal pace along the corridor (W). In-between two blocks of the four tests, the liberation maneuver was applied. With the Epley maneuver (see fig. 7.3) free floating crystals were repositioned into the utricle. In the course of the Epley maneuver, the head was rotated from the Dix-Hallpike position, in which vertigo and nystagmus occurred (fig. 7.3b), by 90 degrees to the Dix-Hallpike position on the other side (fig. 7.3c) and then by another 90 degrees in the same direction (fig. 7.3e). To enable the latter head rotation, the body was rolled to the side position. Finally, the patient was brought up to the sitting position (fig. 7.3f). In all four positions of the Epley maneuver, the head was kept still for at least 30 seconds or as long as the nystagmus lasted.
7.3.4 Protocols

All participants were first required to read the information sheet describing the condition of having BPPV. This document summarized in lay language the causes and symptoms of BPPV, and the therapeutic procedure. Additionally, the document also described the sensor technology and to what extend the subjects' participation in the study would impact the clinical appointment, e.g. the slightly longer duration. Participants were informed that the Epley maneuver does not have any persistent or major side effects.

We asked the participants about their shoe size and provided them with the best-fitting pair of gymnastic shoes. The first experimental block consisted of the four tests described in a previous section while data were recorded by the sensor system. The tests Romberg (R1), Romberg on foam (R2), tandem stance (T) and walking lasted 3 minutes on average. Therapeutic maneuvers were performed immediately thereafter. BPPV patients were treated with the Epley maneuver on the side of the posterior canalolithiasis. Healthy subjects were also exposed to Epley maneuvers, first on the left, then on the right side. The maneuvers were always performed by the same neurologist. In patients, the Dix-Hallpike provocation maneuver was repeated after the Epley maneuver to detect a possible persistence of the positional nys-
(a) The subject is sitting upright.

(b) With his head turned to one side, the subject lays back, his upper body approximately in a 20 degree angle.

(c) The subject turns his head to the opposite side.

(d) The subject rolls to the side his head is turned to.

(e) Still on his side, the subject looks down.

(f) The subject sits up in one fluent motion.

Figure 7.3: Stages of the Epley maneuver to liberate the right posterior semicircular canal.
tagmus. If positional nystagmus was still present, the Epley maneuver was repeated until subsequent Dix-Hallpike maneuvers revealed absence of positional nystagmus.

After successful Epley maneuvers, the three balance tests and the walking test were repeated. Then, the sensor system was switched off and the participants took the gymnastic shoes off.

7.3.5 Analysis

Analysis was based on both the pressure data and the inertial data. Firstly, intervals in the data stream were appropriately labeled and extracted for each subject, i.e. the tests Romberg, Romberg on foam, tandem, and walking before and after the liberation maneuvers. In fig. 7.4 IMU acceleration data are visualized for the three spatial dimensions. Since a subject was required to stand still during Romberg testing (first three tests), the acceleration data did not modulate substantially. Subjects needed to take some steps from ground to the foam mat etc. Thus, these transitions were easily detectable in the data stream. We manually selected the intervals for the individual tests and ensured that only relevant periods were included and no data of a subject moving his/her feet (e.g. in the transition phases).

To address the issue of different shoe sizes of tested subjects, we normalized all data sets to the data size of $20 \times 60$ by linear interpolation. We calculated center-of-pressure (COP) coordinates for all four tests. Additionally, for the walking test, the system automatically extracted the timestamps when the feet made contact to the ground. Two consecutive timestamps defined a step cycle, i.e. stride-to-stride. We did not consider higher-level features such as stance, swing, toe-off and other phases of gait.

In fig. 7.6 different frames during a stance phase are shown for a typical subject. Contact to ground usually started at the heel (fig. 7.6a) and continued until the entire foot touched the ground (fig. 7.6b). Later, the heel lifted off the floor (fig. 7.6c), until, finally, the entire foot was lifted off the floor. We did not impose a specific orientation of the IMU sensor relative to a subject’s shin: it was attached in an arbitrary angle and therefore sensed acceleration along every dimension with an unknown percentage of the total acceleration. We therefore calculated accelerometer magnitude and used this signal for step detection (red curve in fig. 7.5). The peaks of magnitude marked with red circles are impact points, i.e. the time-stamps when a foot made contact to the
7.3. Methods and Material

Figure 7.4: Labeling data samples. Horizontal axis denotes time (i.e. sample index), vertical axis is sensed acceleration.
Figure 7.5: IMU data: accelerometer magnitude in red. Red circles are impact points, blue circles denote toe-off events. The blue bar marks the frame visualized in Figure 7.6c. Data was sampled at 128 Hz.

ground. Blue circles are toe-off events, i.e. the event when the foot left the ground entirely and thus, the signal from the pressure sensor became irrelevant.

COP data and gait data were further analyzed with a moving-window approach. We used 300ms windows with 50% overlap. Similar approaches used smaller window sizes (170 ms) which resulted in false positives on our data [158]. A 300 ms wide window resulted in no false positives. In every window, we computed the parameters listed in Table 7.1.

We performed repeated two-factor analysis of variance, ANOVA ($\alpha = 0.05$, factors = [Group {BPPV, Control}], Condition {pre-, post-therapy})), to test our hypotheses and to derive the relevant parameters. Regarding the analysis for hypothesis H2, we trained and tested the supervised classifiers Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Naïve Bayes (NB), as well as the unsupervised classifiers k-Means (kM) and Gaussian Mixture Model (GMM). The classifiers were trained and evaluated; classification performances were evaluated with 10-fold cross-validation.
7.3. Methods and Material

(a) Initial heel contact.  
(b) Full foot contact.  
(c) Forefoot contact before toe-off.

**Figure 7.6:** Different stance phases of the force data. Feet are oriented top-down: heels are in the top, toes at the lower part of the images.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Symbol</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean($x$)</td>
<td>$\mu(x)$</td>
<td>$1/N \cdot \sum_{i=1}^{N} x_i$</td>
</tr>
<tr>
<td>variance($x$)</td>
<td>$\nu(x)$</td>
<td>$\mu((x - \mu(x))^2)$</td>
</tr>
<tr>
<td>median($x$)</td>
<td>$\tilde{m}(x)$</td>
<td>$x_i : P(x_j &lt; x_i) = P(x_j &gt; x_i) = \frac{1}{2}; \ x_i \neq x_j$</td>
</tr>
</tbody>
</table>

**Table 7.1:** Description of the features; $N$ is the number of elements. $P(k)$ is the probability for $k$.  

7.4 Results and Interpretation

7.4.1 Participants and Data Acquisition

We tested 7 patients (2 m, 5 f) and 9 healthy human subjects (m: 6, f: 3). The patients’ mean age was 60.57 (±9.03) years, the healthy subjects’ mean age was 33.5 (±10.6) years. For the assessment of healthy subjects we scheduled testing sessions on three different days within 2 weeks. Patients’ data were recorded over a period of three months. 3 patients suffered from right-sided posterior canalolithiasis; 1 patient suffered from left-sided posterior canalolithiasis; 1 patient suffered from bilateral posterior canalolithiasis; 1 patient suffered from left-sided posterior and horizontal canalolithiasis; 1 patient suffered from right-sided posterior canalolithiasis and horizontal cupulolithiasis. In two patients, the sensor system only recorded the data of the post-therapy tests for one foot correctly.

Every healthy subject was recorded once before and once after liberation maneuvers; one healthy subject was required to redo the test because the sensor system became non-operational due to low battery power. All patients, except for one, required only one liberation maneuver for successful treatment. One subject suffered from recurrence of BPPV symptoms and was liberated four times. In this patient, to avoid subject-caused bias, we included only data from the first therapy session in our analysis.

Several subjects (patients and healthy) lost balance within the 20 seconds of the tandem tests, T. These events were visible in the accelerometer data and were manually removed such that only stable periods were included for further analysis. However, to avoid learning effects ([159]), we did not repeat the test in these situations.

7.4.2 Data Analysis

For tests R1 and R2 (Romberg) the major COP instabilities appeared mainly in the forward/backward direction (Y coordinate), while for T (tandem), the instabilities occurred in the left/right direction (X coordinate). We used the coefficient of variation, CV, \((\sigma/\mu)\) to estimate the instabilities. CV is a measure of the dispersion of a set of coordinates.

| table 7.2| provides the results of an analysis on the data from healthy subjects. Analysis of data from patients created similar results. Thus, for tests R1 and R2 we further analyzed the Y-dimension of the pres-
7.4. Results and Interpretation

<table>
<thead>
<tr>
<th>Test</th>
<th>CV.x</th>
<th>CV.y</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1, R2</td>
<td>0.143 / 0.182</td>
<td>0.213 / 0.217</td>
</tr>
<tr>
<td>T</td>
<td>0.252 / 0.296</td>
<td>0.190 / 0.192</td>
</tr>
</tbody>
</table>

**Table 7.2:** Coefficient of variation, CV. CV.x or CV.y are the CV values of the X coordinate or the Y coordinate, resp. Larger values are printed in bold. Values are presented as (pre-therapy / post-therapy).

<table>
<thead>
<tr>
<th>Test #</th>
<th>mean</th>
<th>variance</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>24.56 / 25.79</td>
<td>2.481 / 3.219</td>
<td>24.64 / 25.87</td>
</tr>
<tr>
<td>T</td>
<td>11.51 / 11.56</td>
<td>1.37 / 1.667</td>
<td>11.55 / 11.6</td>
</tr>
</tbody>
</table>

**Table 7.3:** Statistical analysis of H1 for tests 1-3 before the therapy. The numbers above are listed as healthy subject / patient values. Significant (p < 0.001) differences are bold.

In the following we address our hypotheses and present the corresponding results.

The first hypothesis, H1, holds that patients and healthy subjects differ significantly in their balance performances prior to any therapy. The Romberg test is a well-known surrogate for bipedal standing performance. We compared patients and healthy subjects during the classical Romberg test (standing with feet together and eyes closed, R1) and its more difficult variations in which subjects are required to stand on a piece of foam (R2, see fig. 7.7a) or on even ground in tandem stance (T, see fig. 7.7b). Results of the statistical analysis of all features are listed in table 7.3. Note the different ranges of values (e.g. insole coordinates) between tests. As we explained above, for R1 and R2 the range of possible values was [1 – 60], for test T the coordinates fell within the interval [1 – 20]. The tables list average values on COP coordinates for all tests R1, R2, T and features (cf. subsection 7.3.3). In table 7.3 the first number represents data from healthy subjects, the second number represents data from patients. Each row contains data for a specific test, e.g. data for R1 are in row 1.

H1 could not be rejected statistically, i.e., there were significant differences of performance between healthy subjects and patients. The mean values and the median values of the COP were significantly lower in healthy subjects than in patients. Thus, healthy subjects kept
their center-of-pressure (COP) closer to the heels than patients. The feature variance did not reveal significant difference between patients and healthy subjects. Interestingly, performance in \( T \), the tandem-stance test, was similar in patients and in healthy subjects: there were no statistically significant differences between the two groups prior to therapy. Whether the small statistically significant differences for \( R1 \) and \( R2 \) are clinically relevant need to be addressed in subsequent studies.

Hypothesis \( H2 \) could not be rejected statistically as well (see \textbf{table 7.4}), i.e., the Epley maneuver affected the patient group. Test performances after therapy were significantly different to performances assessed before the intervention. As a reaction to treatment, patients shifted the mean and median COP significantly closer to the toes. After therapy, mean COP values were approximately 1.5 coordinate counts (\( \approx 7.5\text{mm} \)) closer to the toes in \( R1 \) and \( R2 \). The median shifted similarly. Variance of COP was not affected significantly. Interestingly, there was no noticeable adaption of patients in the tandem test, \( T \). Patients applied a different postural strategy after the Epley maneuver in \( R1 \) and \( R2 \) than after \( T \).
Hypothesis \( H_3 \) holds that the therapy should not have statistically significant effects on healthy subjects. \( H_3 \) was rejected statistically (see Table 7.5). For \( R_1 \), healthy subjects showed no significant reaction to the Epley maneuver. However surprisingly, healthy subjects showed a statistically significant reaction to both \( R_2 \) and \( T \). In \( R_2 \), healthy subjects shifted the mean and median COP slightly towards the heels (~0.7 coordinates = 3 mm). Whether this small, but significant difference is clinically relevant, should be addressed in subsequent studies. A stronger reaction to the Epley maneuver was seen in tandem test \( T \). Data suggested that healthy subjects tried to stabilize the tandem stance by shifting the mean and median COP towards the lateral side of their feet. On average the COP shifted about 1.5 coordinates (7.5 mm) towards the lateral side. Figure 7.8 visualizes typical examples during the tandem task. In figure 7.8a, the mean pressure during \( T \) of a healthy subject is shown, while in figure 7.8b, mean data during \( T \) in a patient is depicted. The two images are representative for the statistical evidence presented above: after the Epley maneuver, for the tandem task, healthy subjects shift their COP to the lateral side of the feet; patients, however, did apply different strategy.

As discussed above, both groups showed reactions to the Epley maneuver, but both had different compensation mechanisms. Healthy subjects shifted their COP in the backward direction, while patients shifted it forward towards the toes. Further, the range of COP coordinates (range = [min, max]; see Table 7.6) in healthy subjects changed not significantly after the Epley maneuver whereas in patients the sway increased significantly for both tests. Overall, patients showed

### Table 7.4: Statistical analysis of \( H_2 \) for tests 1-3 for patients. Numbers represent as (before / after) means. Significant (\( p < 0.001 \)) values are bold.

<table>
<thead>
<tr>
<th>Test #</th>
<th>mean</th>
<th>variance</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_1 )</td>
<td>25.79 / 27.21</td>
<td>3.219 / 3.218</td>
<td>25.87 / 27.28</td>
</tr>
<tr>
<td>( R_2 )</td>
<td>25.93 / 27.43</td>
<td>3.889 / 3.888</td>
<td>25.99 / 27.5</td>
</tr>
<tr>
<td>( T )</td>
<td>11.56 / 11.69</td>
<td>1.667 / 1.858</td>
<td>11.6 / 11.74</td>
</tr>
</tbody>
</table>

### Table 7.5: Statistical analysis of \( H_3 \) for tests 1-3 for healthy subjects. Numbers represent as (before / after) means. Significant (\( p < 0.001 \)) values are bold.

<table>
<thead>
<tr>
<th>Test #</th>
<th>mean</th>
<th>variance</th>
<th>median</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_1 )</td>
<td>24.56 / 24.71</td>
<td>2.481 / 2.482</td>
<td>24.64 / 24.79</td>
</tr>
<tr>
<td>( R_2 )</td>
<td>25.33 / 24.63</td>
<td>3.351 / 3.350</td>
<td>25.41 / 24.74</td>
</tr>
<tr>
<td>( T )</td>
<td>11.51 / 9.997</td>
<td>1.37 / 1.868</td>
<td>11.55 / 10.04</td>
</tr>
</tbody>
</table>
Figure 7.8: Comparing stabilization strategies of a healthy subject (left) and a patient after the Epley maneuver. As analysis revealed healthy subjects shift the mean COP towards the lateral arch of their feet while patients fail to do so.

Table 7.6: Changes in range of COP data in healthy (subscript H) and patients (subscript P). For the tests R1 and R2 COP Y-coordinates were analyzed. All differences in the patients group were statistically significant with \( p < 0.05 \). Values are presented as pre- / post- therapy.
Table 7.7: Classifier performances on healthy subjects’ data. Results of the best classifier are bold.

<table>
<thead>
<tr>
<th>Test #</th>
<th>SVM</th>
<th>kNN</th>
<th>Naive Bayes</th>
<th>GMM</th>
<th>k-Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>89.8012</td>
<td>81.2716</td>
<td>61.973</td>
<td>48.1417</td>
<td>51.3984</td>
</tr>
<tr>
<td>R2</td>
<td>79.0258</td>
<td>80.0398</td>
<td>59.7217</td>
<td>51.0934</td>
<td>50.9294</td>
</tr>
<tr>
<td>T</td>
<td>83.4409</td>
<td>87.4946</td>
<td>62.9351</td>
<td>47.6344</td>
<td>50.1882</td>
</tr>
</tbody>
</table>

Table 7.8: Classifier performances on patients’ data. Results of the best classifier are bold.

<table>
<thead>
<tr>
<th>Test #</th>
<th>SVM</th>
<th>kNN</th>
<th>Naive Bayes</th>
<th>GMM</th>
<th>k-Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>91.7247</td>
<td>91.835</td>
<td>78.5864</td>
<td>51.3066</td>
<td>50.4843</td>
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<tr>
<td>R2</td>
<td>86.4986</td>
<td>87.2076</td>
<td>73.2638</td>
<td>50.7651</td>
<td>51.1206</td>
</tr>
<tr>
<td>T</td>
<td>78.0059</td>
<td>88.0227</td>
<td>65.6311</td>
<td>48.4848</td>
<td>51.2512</td>
</tr>
</tbody>
</table>

used by the algorithms. Table 7.9 shows the results of the classifiers. For R1, SVM performed slightly better than the other classifiers. However, for R2 and T kNN showed a better performance. With a mean accuracy of approximately 80% kNN outperformed the other classifiers.

7.4.3 Other Findings

Analysis of the time stamps during the walking task did not reveal any significant differences between healthy subjects and patients. This did not match our expectations since imbalance could result in changes of walking speed ([160, 161]). We assume, however, that the discrepancy between these data and our expectations maybe caused by the way we assessed walking speed. In order to be able to prevent a subject from falling, one of the authors was walking close to the subjects. We believe that the subjects subconsciously adapted their walking speed to match the speed of the experimenter, even though we asked them

<table>
<thead>
<tr>
<th>Test #</th>
<th>SVM</th>
<th>kNN</th>
<th>Naive Bayes</th>
<th>GMM</th>
<th>k-Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>86.3833</td>
<td>86.1256</td>
<td>51.0232</td>
<td>46.6609</td>
<td>50.3981</td>
</tr>
<tr>
<td>R2</td>
<td>75.4253</td>
<td>76.8984</td>
<td>63.3925</td>
<td>52.6465</td>
<td>49.3667</td>
</tr>
<tr>
<td>T</td>
<td>68.5773</td>
<td>78.6738</td>
<td>65.8821</td>
<td>50.4606</td>
<td>52.1894</td>
</tr>
</tbody>
</table>

Table 7.9: Classification performance for different classifiers on H3. Result of the best classifier for each test (1-3) is highlighted with bold font.
to walk at a fast, but freely chosen speed. We will address this in future studies.

7.5 Conclusion and Outlook

In this work we introduced a system for automated Romberg testing and demonstrated its feasibility with an investigation on the effects of a treatment for Benign Paroxysmal Positional Vertigo (BPPV). In prior work, it has been reported that patients suffered a temporary exacerbation of their subjective postural imbalance following an Epley maneuver [92] [162] [163]. So far, this effect was not further investigated. In this work, we investigated three hypotheses. We could not reject statistically the first hypothesis, $H_1$: patients with BPPV and healthy subjects differ significantly in their bipedal performance. We also could not reject statistically $H_2$: the Epley maneuver provoked a measurable and statistically significant change of bipedal-performance features in patients. However, we could reject $H_3$ statistically: the Epley maneuver also had a statistically significant effect on bipedal performance in healthy people. We used a sensor system measuring inertial data and force applied to the feet in order to assess the bipedal performance of the subjects. We recorded data from 7 patients and 9 healthy subjects. Inertial data and force data were statistically analyzed and classifiers were trained.

Patients differed significantly from healthy subjects, i.e. the impact of BPPV was measurable. The Epley maneuver affected the bipedal performance of patients. However, there was, unexpectedly, a statistically significant difference between the performance of healthy subjects before and after the Epley maneuver. The control subjects adapted a different stabilization strategy than patients, however.

One limitation of this study was the significant age difference between patients and control subjects. The age differences could have introduced differences in pre-treatment postural values and differences in response to liberation maneuvers.

Based on our findings, we plan future studies addressing these effects. As we introduced in the motivation it could be helpful if the severity of BPPV, the efficacy of the treatment and other therapy related parameters could be estimated by an automated system. Such a system possibly could assist as a diagnosis tool for better matching a therapy schedule to individual needs of individual patients. The
duration of treatment could be reduced and the overall efficacy of treatments could be increased.
In this chapter, we present a study in weightlifting athletes. We analyzed the accuracy of movement timings for a standard, yet complex barbell movement. We used IMU data to classify the athletes according to their experience and the quality of execution of the exercises given expert labels.

This chapter was published in Body Sensor Networks, 2013 titled Experts lift differently: Classification of weight-lifting athletes [70].
8.1 Abstract

The process of learning novel body movements exposes a student to multiple difficulties. Understanding the range of motion is fundamental for learning to control the involved body parts. Theory and instructions need to be mapped to body movements: a student not only needs to mimic or copy the range of motion of individual body parts, but he also needs to trigger the motion fragments in the correct order. Not only correct order is important, but also precise timing. If the movements in questions are intensified by additional load, optimality of the motion patterns becomes crucial. Sub-optimal execution of an exercise reduces the performance or can even induce failure of completion. Correct execution is a subtle interplay between the correct forces at the right times. In this paper, we present a sensor system that is able to categorize movements into multiple quality classes and athletes into two experience classes. For this work we conducted a study involving 16 athletes performing squat-presses, a simple yet non-trivial exercise requiring barbells. We calculated various features out of raw accelerometer data acquired by two inertial measurement units attached to the athletes’ bodies. We evaluated exercise performances of the participants ranging from beginners to experts. We introduce the biomechanical properties of the movement and show that our system can differentiate between four quality classes ("poor", "fair", "good", "perfect") with an accuracy above 93% and discriminate between a beginner athlete and an advanced athlete with an accuracy of more than 94%.

8.2 Introduction

Learning novel mental or physical skills is an iterative process. Depending on knowledge, experience, and talent, the time required until an individual's performance matches the requirements for a skill varies. Common to both mental and physical learning is a repetitive comparison of the performance to a model or target of the skill. The subject has to decide up to which magnitude or precision a deviation from the optimum is acceptable. For example: in a vocabulary learning task (i.e. learning a specific number of words by heart) the optimum would be a 100% correct recall rate, while a performance of 80% would be acceptable for a student who only wants to pass a test. Or,
for example, a person learning to bike will only accept a 100% success rate of not falling off the bike under normal conditions.

We define two kinds of target performances: Skills that require a 100% success rate in order to be performed effectively are further on dubbed "discrete skills" (e.g. biking without falling off, remembering a phone number etc.). On the other hand, there are "continuous skills" (e.g., learning a set of words) i.e. skills that can be completed successfully without requiring perfection.

In this work, we are focusing on continuous physical skills in the context of weightlifting. Different to discrete physical skills in other sports, in weightlifting the most movements comprise a complex motion sequence executed by translating external load (barbell with weights) against the vector of gravity. If a subject has incorporated the complex movement pattern and is able to reproduce it to a certain degree of fidelity, he will be able to move a weight along a prescribed path into a targeted end position. However, accuracy of timing, and linked to that accuracy in position are usually low for beginners and increase only with training. Directly linked to the accuracy of timings and motion paths is the maximum weight an athlete will be able to move into the target position: the more accurate an athlete’s execution of the movement is the more weight he will be able to lift successfully. In the following, we are not interested in absolute strength, but rather in accuracy and precision of a subject performing a given movement. This allows us to compare different athletes based on their skill level rather than on their strength. Using strength as a feature, i.e. weight that can be moved successfully, a very strong person would always outperform a very weak one, even if he performed the technique very badly and the weaker subject was an expert.

Learning complex continuous physical skills is often difficult by nature and even more so if practiced alone. Often the only feedback an athlete gets is success or failure of completion, but sometimes not even that. However, as we have motivated above, the movement pattern was probably performed successfully, but with a lack of accuracy. Solutions to that are video-based analysis tools allowing a subject to watch his performance afterward, or an expert coach directly reporting back cues for a better execution of the exercise. The former approach usually has the drawback of requiring large user interaction (controlling a video recorder or similar), but providing strong identificability to an athlete since he sees herself performing. On the other hand, the feedback from a coach usually arrives instantaneously, however, com-
communication issues or a lack of immersion can diminish the effect of coaching.

In this work, we present a first step towards an automated training assistance tool for weightlifters that only requires sensor data from inertial measurement units (IMU). We present a sensor-driven evaluation of athletes performing a basic movement often (but not exclusively) seen within functional fitness context: "Thrusters". A thruster is by definition a squat followed by a press of a barbell into an overhead position (see Fig. 8.1). Our system automatically detects instances of these movements, extracts features of interest and classifies the individual instances (ground-truth labels were assigned by a trained coach). Our system is able to classify the instances into four different groups with an success rate of above 93%. The system is further capable of discriminating beginner athletes from advanced athletes with an accuracy above 94%.

8.3 Related Work

There are only few approaches for objective and automated skill analysis in sports. Most automated solutions target training logs and record the work performed, e.g. Garmin [164] (GPS), Suunto [5] (acceleration sensors etc.), Nike [165] (activity tracking with accelerometers). The problem exposed to us in this context is more complicated than activity detection since we need to know with high precision the quality of a specific activity.

In running, there are various attempts to classify runners using IMUs: Strohrmann et al. [121] focused in their work on runners at various experience levels. They showed that a smart phone attached to a runner’s upper arm can help him gaining proficiency in running by providing vibro-tactile feedback if his upper-body moves too much.

In cycling, automated training tools exist that support an athlete in improving his biking technique. Apart from video-analysis that is mainly used off-line, there are solutions that put sensors in pedals, saddles, other bike components, e.g. by Rotor [166]; there are also enhanced ergometers, e.g. Wattbike [167], that incorporate multiple sensors. These tools report the distribution of work among the two pedals, the current power output etc. Usually, athletes are connected to a heart-rate belt; fusing the different data sources opens possibilities for accurate performance tracking and training-progress surveillance.
Stapelfeldt et al. [168] evaluated various systems targeted at providing objective performance data.

In rowing, Gravenhorst et al. [169] and Tessendorf et al. [170] used IMUs to analyze temporal features, but also spatial features of the movements of the oars. They analyzed also the motion and orientation of the boat during activity and showed that is feasible to create a training tool with IMUs alone.

We are not aware of any IMU-based approach for improving weight lifting movements. Video-based tools such as Coach’s Eye and Ubersense [171, 172] attempt to reduce the issue of immersion by video-based interfaces for performing frame-by-frame analysis of a target movement.

All solutions presented above provide limited automatic means of generating feedback or even classifying the movement quality. In our work, we aimed at closing that gap by contributing to a weight-lifting training tool with direct automatic feedback.

8.4 Study Description

In this work, we analyzed a basic exercise in the context of functional fitness: A thruster is a multi-joint movement during which an athlete aims at translating a barbell from a racked shoulder position over a squat (fig. 8.1a) into an overhead position (fig. 8.1d). For exercise, this movement is repeated multiple times without stopping in-between. Optimally, from a bio-mechanical perspective, the barbell should move in one continuous motion from the squat position into an overhead position. Horizontal displacement should be avoided as it might induce inferior joint angles on the athlete, reduce hereby his performance or even increase the risk of injury.

For a correctly executed thruster, the initial and main impulse originates from the leg and lower back muscles.
At the maximal hip extension, the momentum of the barbell should be exploited as the athlete pushes the weight up the remaining path using his arms. Timing is critical at the point of transfer, where the main workload is shifted from the legs and lower back to the arms. If an athlete pushes to early with his arms he, actually dampens the barbell movement – as a consequence of having to detach the barbell from the body. This not only reduces the effect of the hip movement, it also adds substantial load to the shoulder muscles. If, however, an athlete pushes too late, he loses a large part of the energy already invested in moving the barbell upwards. It is intuitively clear why horizontal motion does not have any benefit for an athlete, unless biomechanically enforced (due to, e.g., limited flexibility). The optimal thruster movement can therefore be described as a two-phased squat/press move where the transition between lower-body work and upper-body work (see fig. 8.1c) needs to be as smooth as possible. According to several experts’ experiences, the errors seen most often in beginners and in athletes with limited experience are sub-optimal transition phases and too weak acceleration – executing the movement not sufficiently aggressive.

For this exploratory study, we asked athletes to participate prior to their regular training. Everybody in a training schedule needs to be healthy, hence, we limited our questionnaire to demographics, physiological and training parameters. In every class, the level of experience ranges from absolute beginners performing this sport for less than three months to experts that are training these movements for more
than two years. The features for our algorithms were independent of the barbell weights, i.e. an athletes’ absolute power output. Instead, we based our feature calculation on acceleration values of two sensors and their inter-sensor synchronization.

We have chosen a unobtrusive sensor setup for mainly two reasons. An optical system, e.g. Vicon [12], would have provided us probably with more accurate data, also reporting 3D positions of individual body parts. However, setup time would have been prohibitive for fast testing and also setting up a camera rig inside a training facility was not preferable. Second, we envision a mobile sensor system that at one point can be used at any location without needs for complex setups. We therefore favored inertial measurement units (IMUs) (see [65,109]) which are optimal in a trade-off of accuracy vs. setup complexity. The IMUs are small (1.45 cm × 4.5 cm × 0.5 mm), light-weight (approx. 21.7 g, including casing and battery) and can be fully controlled remotely using a smart-phone or PC application.

![Image](image.png)

**Figure 8.2:** Sensor locations: wrist, hip and ankle.

We equipped each athlete with three sensor devices: on the left ankle, on the lower back, attached with a belt and on the left wrist, see **fig. 8.2**. The athletes were asked to perform three sets of thrusters at a freely chosen weight. The first two sets consisted of ten thrusters with a barbell weight, \( w_{BB} \), allowing the athletes to perform the exercise at
the best of their skill level. We allowed the athletes two minutes of rest between each set. For the last set we did not specify the number of repetitions, but asked every athlete to load the barbell with a 3 repetition max (3 RM) weight; a weight they considered light enough to be able to perform three thrusters, but possibly not a fourth one. The last set aimed at providing data for exhaustion detection.

We recorded every athlete with a smart-phone camera; this video footage was used later for labeling the individual thruster instances.

From every athlete we recorded demographic data (age, sex) and experience level for functional fitness in general. We further recorded their body weight ($w_B$), body height, squat depth and arm length. As an incentive for the athletes, we provided them with information on their power output, hence we needed the body parameters listed above.

### 8.5 Study Evaluation

#### 8.5.1 Questionnaire and Data Recording

Prior to starting the session, we noted from every athlete age and gender. Further, we asked them about the experience level, ranging from 0: (beginner; less than 3 months of experience) to 4 (expert, more than 3 years of experience and/or coaching education). The athletes’ body weight, body height, vertical distance of hip joint between a squat position and upright position, and arm length were also recorded.

For each set we noted the barbell weight including additional weight plates. The athletes could freely choose the start of their first set; our data recording system automatically synchronizes video stream with sensor data.

In order to report the average power output to the athletes, we needed their squat depth and arm length. We used the NASA database [29] to approximate the upper-body weight, $w_U$ ($N$). Fig. 8.3 illustrates the body parts included. The upper-body contributes to 72.7% of a standard human’s (50th percentile) body mass. We defined this value as $\rho_{\text{upper}} = 0.727$, hence, $w_U = w_B \cdot \rho_{\text{upper}}$. 
Work (Joule) is defined as $W := \text{force (N)} \times \text{distance (m)}$; the distance the barbell has to travel is the squat length plus the arm length, $\ell_S + \ell_A$. Adding the parts together, the work for one thruster is

$$W_{\text{thruster}} = (\ell_S \cdot (w_U + w_{BB}) + \ell_A \cdot w_{BB}) \cdot g \quad (8.1)$$

Athletes usually are interested not only in their maximal work capacity, but also in their power output. The definition of power, $P = W/t$, was used to report the participants’ average power output.

### 8.5.2 Classifying Thrusters

#### Instance Extraction and Labelling

It was our goal to automatically discriminate between well-executed and suboptimally performed thruster instances. Ground-truth labels for individual thruster instances were assigned with the help of a regular video player featuring frame-by-frame control by a certified coaching expert. The range of labels were \{0: failure; 1: poor; 2: fair; 3: good; 4: perfect\}. Additional to the labels by the experts, we tested three others resulting in the four label groups:

1. labels assigned by an expert to each thruster instance as described above,

2. mean expert-assigned labels of all 10 instances (rounded to the nearest class),
3. self-reported experience level of the athletes (from the questionnaire),

4. reducing to two-classes from the expert labels (poor and good):  
   \{1, 2\} \rightarrow 0; \{3, 4\} \rightarrow 1

For every athlete, we used accelerometer data from the wrist and hip IMUs. Data from the ankle sensor was neglected since it did not provide relevant information; feet motion was only noticed occasionally. The data was analyzed using MATLAB. Due to the properties of the sensor attachments (velcro) the devices could move relative to a subject’s body; this was anticipated. We used the magnitude of the accelerometer signal as raw data for our analysis since it is unaffected by sensor orientation (acceleration magnitude $\bar{a} := \sqrt{x^2 + y^2 + z^2}$).

Our sensor system detected the episodes of thrusters automatically. An episode of thrusters manifests itself by an increased variance within a window of about 1 second; in-between two episodes the athletes did not perform any fast movements. A one-second window acts as a low-pass filter with a sufficiently short lag. Using a empirically found threshold value, our algorithm could automatically derive the starting and ending indices of each thruster episode, see [fig. 8.4].
Figure 8.4: Thruster episodes, inside yellow box, are automatically detected. This plot shows data from the hip sensor. Blue: original data; blue: smoothed data. Sampled at 128Hz.
Thruster Modelling

We aimed at creating a system that can calculate non-trivial features autonomously. The raw accelerometer magnitude contains by nature too much noise for reliable unsupervised feature calculation — mainly due to the way the sensors were attached to the body. To cope with this difficulty, we decided to create a biomechanically-inspired accelerometer-response model that could be fitted to the real data. Calculating features on the fitted model alleviated the aforementioned problems.

Inspired by literature on biomechanics (e.g. [173, 174]) and after discussions with coaching experts on the biomechanic properties of the exercise, we decided to model the accelerometer magnitude response of an individual thruster execution with a sum of 6 Gaussian functions. Handling a sum of Gaussian was preferable over, e.g., a polynomial model of high order (e.g. 5). From our discussions we derived that a single thruster instance consists of two main peaks (hip/arm work) and one minor peak (dipping phase) that are interspersed with three "valleys" (initial squat, transit, turning-point). Hence, a sum of six Gaussian with positive and negative scales was an approximation to the real world that the coaching experts could agree about. The final model was:

\[
t(x) = \sum_{i=1}^{6} \alpha_i \cdot \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}} - \beta_i
\]

(8.2)

Each of the Gaussians has four parameters: scale \( \alpha_i \), amplitude offset \( \beta_i \), standard deviation \( \sigma_i \), and mean value \( \mu_i \). We derived the initial values by first calculating a mean thruster out of 50 instances of different athletes and then fitting our thruster model to it. The resulting template curve for an instance of a [thruster] can be seen in fig. 8.5.
Figure 8.5: Accelerometer signal (blue) and fitted template (red) of a thruster instance. Sampled at 128Hz.

Thruster Extraction

Within each episode of 10 thrusters, a peak detection algorithm found the center peaks of the thruster instances. For each peak found, an interval of 1.5s bracing the peak was extracted from the accelerometer data. A non-linear optimization (the Nelder-Mead simplex direct search implemented in MATLAB’s fminsearch function) was used in order to find the parameters to the thruster model. Since hip and wrist sensors were synchronized, we could also compare the time differences of the peaks at the hip with the peaks from the wrist sensor and used this time difference as an additional feature. A model fitted to the data also provided us with the positions of the two main peaks, the amplitude of all the Gaussians etc.
Figure 8.6: Showing the acceleration magnitude, $\tilde{a}$, and features calculated on the model (not shown): First to fourth phase (light red and light blue area), sample thruster interval (yellow area), work for hips (blue area), work for arms (red area); red curve: arm sensor, blue curve: hip sensor. Data was sampled at 128 Hz.
Additional Features and Classification

We also calculated the variance for the 1.5 seconds bracing a thruster, the normalized work, and hip/arm work ratio after expert coaches suggested these features to be considered (also see fig. 8.6 for a visualization). Since they were computationally simple to calculate we agreed to add them to our analysis.

We trained a support vector machine (SVM) [113] on 75% of the data to learn the labels and tested it on the remainder.

We wanted to find the subset from our full set of features that is as small as possible for the maximal performance. Hence, we tested for every subset the classification performance and selected the ones resulting in the best classifier performance.

![Figure 8.7: Classifier performance (Y-axis) for different feature set sizes (X-axis). The height of the columns represents the numbers of classifiers with a given classification accuracy.](image)

Physical Performance Analysis of and for the Athletes

The incentive for the athletes to participate in our study was for one part the possibility to be analyzed thoroughly by a coaching expert, but also to get a quantitative report on their physical performance. From the questionnaires, we extracted the values of the squat depth, arm length, body weight, and barbell weight (see table 8.1 and table 8.2). For every athlete we calculated the work performed for one thruster.
instance using equation 8.1. We are aware that this is an approxima-
tion to the real work performed, but it was sufficient as an objective
feedback to the athletes.

8.6 Results

8.6.1 Demographics and Body Parameters

16 athletes participated in the study. Table 8.1 lists the demographic
data. The statistics of body parameters and work capacity of the ath-

<table>
<thead>
<tr>
<th></th>
<th>Female</th>
<th>Male</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>no. athletes</td>
<td>4</td>
<td>12</td>
<td>16</td>
</tr>
<tr>
<td>weight, (kg) ($w_B$)</td>
<td>60.25 (0.50)</td>
<td>82.30 (6.85)</td>
<td>76.81 (11.49)</td>
</tr>
<tr>
<td>height, (cm)</td>
<td>166.25 (2.75)</td>
<td>178.08 (5.03)</td>
<td>175.25 (6.76)</td>
</tr>
<tr>
<td>experience</td>
<td>2.00 (1.44)</td>
<td>2.83 (0.83)</td>
<td>2.63 (1.02)</td>
</tr>
</tbody>
</table>

Table 8.1: Demographics for females, males and overall:
Mean values; (± standard deviation).

letes are listed in Table 8.2: arm length ($\ell_A$), squat depth ($\ell_S$), chosen
weight ($w_{BB}$), and work performed ($W_{thruster}$).

<table>
<thead>
<tr>
<th></th>
<th>Female</th>
<th>Male</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>squat len., (cm)</td>
<td>42.50 (5.00)</td>
<td>47.91 (3.96)</td>
<td>46.56 (4.73)</td>
</tr>
<tr>
<td>arm len., (cm)</td>
<td>56.25 (6.29)</td>
<td>62.50 (3.54)</td>
<td>60.75 (4.93)</td>
</tr>
<tr>
<td>barb. weight, (kg)</td>
<td>18.75 (2.50)</td>
<td>39.17 (3.43)</td>
<td>34.05 (9.66)</td>
</tr>
<tr>
<td>work (J)</td>
<td>352.4 (31.5)</td>
<td>702.1 (44.5)</td>
<td>627.1 (154.4)</td>
</tr>
</tbody>
</table>

Table 8.2: Biomechanical parameters for the thrusters:
Mean values; (± standard deviation).

8.6.2 Feature Analysis and Classification

After labeling, we compared each athlete’s self-reported experience
level to the average thruster level assigned by an expert. The cor-
relation was significant with a correlation coefficient of 0.5336 ($p =
0.001$). We can therefore state that – in general – the athletes’ self-
classification matches an expert’s judgment on their exercise quality.

The thruster episodes were detected reliably, with a success rate
of 100%. It has to be noted, however, that athletes were not allowed
to walk or use their arms intensively in-between the episodes for our detection to work.

The acceleration signals matched the thruster template well, i.e., the parameters could be fitted with small errors between model and data for experienced athletes. For less experienced athletes, we noted a decreased ratio between the accelerometer magnitude during a thruster move and during other body movements. We attribute this fact to stronger un-controlled and un-necessary movements during execution of the exercise by an less experienced athlete. As a consequence, the model parameters were less reliably found and the error values increased accordingly. In table 8.3 we list for different athlete groups the mean variance for the thruster instances; it reflects the increased power output of the more experienced athletes. This can also be seen in fig. 8.8 where we show two classes (beginners and advanced athletes) with the separating plane from a linear classifier.

<table>
<thead>
<tr>
<th>Experienced Athletes (3,4)</th>
<th>Novice Athletes (0-2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance</td>
<td>0.613</td>
</tr>
<tr>
<td>Variance</td>
<td>0.508</td>
</tr>
</tbody>
</table>

Table 8.3: Variances (normalized) for thruster models for different athlete groups (self-reported).

Figure 8.8: Variance vs. Scale features for advanced athletes (green data points; labels {3,4}) and beginner athletes (red data points; labels {1,2}).
For automatic classification of the thrusters, we trained an SVM on a sub-set of all thruster instances. We have chosen randomly 75% of the samples to train the classifier. Based on our analysis (see fig. 8.7), we used the following features: Model errors, data variances, ratio of normalized hip-work vs. normalized arms-work. The remaining 25% were then used for testing the accuracy of the SVM. We let the training/testing procedure run for 100 iterations: every time a different set of instances was selected for training and testing.

We tested different sets of labels on their impact on the classifier performance (see section 8.5.2): first, we used the self-reported experience level; we also used the expert-provided labels for each thruster instance. Further, we tested whether the average thruster amplitude per episode per subject provided better results. Table 8.4 lists the respective accuracies: the two-class problem (beginners/advanced) performs best; self reported levels represent best the detailed quality (1-4) of the thrusters, the mean expert levels are only slightly less accurate. Per-thruster expert levels were the most difficult to model with an SVM using the features presented.

<table>
<thead>
<tr>
<th>SVM-Classifier Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-class Separation</td>
</tr>
<tr>
<td>Self-reported Levels</td>
</tr>
<tr>
<td>Mean Expert Levels</td>
</tr>
<tr>
<td>Expert Levels</td>
</tr>
</tbody>
</table>

Table 8.4: Success rate of SVM classifier in % for three different labellings.

Our system is able to differentiate between experts and beginners solely using two IMUs with an accuracy above 94%. Classifying individual thruster instances can be achieved using the same setup at an accuracy of above 93%.

8.7 Conclusion and Outlook

In this work, we presented results from a study analyzing a basic exercise in the functional fitness regime: thrusters. We analyzed the movements of 16 athletes. Employing expert input and applying physics, we defined an accelerometer-magnitude model for the exercise in question.

In our analysis, we fitted the parameters of our model to each thruster instance. Using that analytical model, we calculated fea-
tures for a SVM classifier. The classifier performed best with the self-assigned experience levels as ground truth (93% correct). Per-thruster expert levels yielded above 80% classification performance, while average expert levels resulted in more accurate classification. The system was further capable of classifying the exercise instances with an accuracy of more than 94% into two classes: beginner and experts.

In analysis we calculated – as a chief incentive for the athletes to participate – the subjects’ average power output per thruster.

We want to transfer the algorithms from back-end applications (MATLAB) into real-time, online feature and classification calculation routines running on the IMU devices. Since we showed that is possible for an IMU-based setup to classify the execution of thruster movements into four different quality categories, we believe a "virtual coach" is feasible that supports athletes and coaches in analyzing exercises. From our experience we believe that for body movements similar to thrusters in range of motion and speed, the number of modalities and sensor devices suffices. However, for more complex movements and/or increased expressiveness of an automated system additional modalities might be required.
In this chapter, we present a study that analyzed the effects of warm-up routines and of stretching routines on the center-of-pressure features in weightlifting athletes.

This chapter was accepted for publication in *BioMed Central Research Notes* titled *Effects of Stretching and Warm-Up Routines on Stability and Balance during Weight-lifting: A pilot investigation* [71].
9.1 Abstract

Background  The efficacy of warm-up and stretching in weight-lifting remains unknown, especially for the weight-lifter’s stability and balance during lifting.

Methods  13 subjects were randomly assigned a 10-minute stretching routine (SR) or a 10-minute warm-up routine (WR) and compared against 5 controls (no stretching or warm-up). Before and after the individually assigned routine, the participants’ centre of pressure (CoP) was assessed using plantar-pressure sensors. The subjects were measured during 10 repetitions of air squat (no load, "AS"), front squat (FS; 20kg/15kg bar), overhead squat (OHS; m: 20kg / f: 15kg bar), and a deadlift lifting exercise ("DL"; 20kg/15kg bar). The impact on CoP dynamics of the warm-up and stretching routines were examined with repeated two-factor analysis of variances (ANOVA) of the mean and the coefficient of variance (CV, shown in %), as proxies for stability and balance.

Results  After stretching, the SR athletes shifted the mean CoP towards the toes ($\approx 1cm; p < 0.01$) while the WR athletes shifted the CoP towards the heels ($\approx 1cm; p < 0.01$) during AS. For the remaining exercises, the SR athletes shifted the CoP towards the heels (between $0.8cm$ and $5.7cm$) compared to WR ($\approx 1.9cm$ towards the heels in FS, no significant change in OHS ($\approx 1mm$) and DL ($\approx 3mm$)). The controls did not show any change between pre- and post-datasets. After stretching, the CV decreased for the AS and OHS exercises (AS: 10.2% to 7.0%, OHS 9.8% to 7.8%), but increased after WR (AS: 7.1% to 10.1%) or did not change significantly (OHS). Both WR and SR resulted in increased CV values for FS and DL. No change of CV was observed in the controls.

Conclusions  SR had a stronger impact on CoP during the assessed exercises than either WR or controls. A reduction in CV after SR exercises (AS, OHS) suggests a clear improvement in stability and balance during weight-lifting. The lack of a significant effect for complex movements (OHS) suggests only a limited effect of a 10-minute warm-up routine on CoP features. 10 minutes stretching might therefore be more efficient for improving stability than a general 10 minute warm-up.
9.2 Introduction

The purpose of warm-up (WR) and stretching (SR) routines is to increase the range of motion (RoM) of skeletal muscles and the associated connecting tissue surrounding the joints, and thus to improve RoM of the exercise-specific kinematic chain [175, 176, 177]. An improvement in range of motion enables athletes to adopt more optimal positions during weight-lifting and thus to exploit the muscular/strength capabilities [178, 50, 179]. The concept is clearly demonstrated in fig. 9.1 where the athlete needs to extend her arms further backwards in order to achieve a balanced posture (fig. 9.1a). The result is increased torque in various parts of her body, especially the shoulder joint [180]. In contrast, the athlete in fig. 9.1b showed a superior RoM and was thus able to maintain a bio-mechanically more optimal position. On the other hand, negative side effects such as a reduction of peak force up to 8% have been demonstrated to be caused by static stretching [181]. As weight-lifting athletes are cautious not to trigger detrimental effects to their maximal strength, static stretching is often avoided [182, 96]. Alternative techniques such as dynamic stretching, proprioceptive neuromuscular facilitation, and self-myofascial release have been shown to not affect peak strength negatively whilst bearing the positive effects of static stretching [183, 97, 98]. It has also been shown in related work that stretching can improve the balance performance of athletes [184]. Athletes with good stability seem to be able to control the barbell better in extreme poses, e.g. in the bottom of an (overhead) squat. However, elite athletes often fail lifts in extreme positions (e.g. at the bottom of a squat) due to a lack of balance [53]. Thus, stability and balance seem to be key parameters for control during weight-lifting and for successfully performing advanced lifting exercises. However, the role of stretching or warming-up prior to lifting exercises, especially on the stability of the centre of pressure and the subject’s balance during lifting, remains unknown. It is plausible that despite playing a positive role in enhancing the range of motion, negative side effects regarding stability and balance are caused by warm-up or stretching. Analysis of centre of pressure (CoP) data acquired from plantar pressure sensors allows dynamic postural parameters e.g. balance to be estimated. Data from such approaches also suggest that a subject’s CoP is correlated to changes in RoM [185, 186]. The goal of this study was to compare general warm-up with stretching that is focused on joints and muscles that are involved
in basic weightlifting exercises in order to assess the role warm-up or stretching on static and dynamic measures of stability and balance during weight-lifting. An additional aim of this study was to evaluate the applicability of the sensor system in weightlifting settings. Three questions were asked in this study:

1. Does stretching alter features of CoP?
2. Does moderate warm-up alter features of CoP?
3. Are there differences between the effects of warm up and stretching for stability during weight-lifting?

9.3 Methods

In this study, several exercises were analysed. The air squat (AS, fig. 9.2a) is a squat without any external weight. In the overhead squat (OHS, fig. 9.2b) an athlete balances a barbell above his head with straight arms while performing a squat. During the front squat (FS, fig. 9.2c) the athlete has the barbell on his shoulders. The deadlift (DL, fig. 9.2d) is not a squat exercise since the barbell starts from the ground and finishes at hip height. However, in this study, an aim was also to
understand the differences between warm-up and stretching routines on CoP features during different lifting exercises.
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Exercise an athlete is required to start in the black pose, reach the blue pose and finish in the black pose again.

Figure 9.2: The four exercises. The different colors represent different key-poses that have to be reached. To successfully perform an exercise an athlete is required to start in the black pose, reach the blue pose and finish in the black pose again.
9.3.1 Subjects
Thirteen athletes (mean age $28.2 \pm 5.9$ yrs) from a local functional training facility volunteered to be analysed in this study and underwent either stretching or warm-up exercises. In addition, 5 subjects were tested without stretching or warm-up exercises in order to provide a control. Inclusion criteria were an age between 18 and 75, no medical issues affecting their physical performance, and no prior training on the day of testing. The study was approved by the Ethics Committee of the ETH Zurich, Switzerland, for which all participants signed a form of consent in order to participate. All athletes were also required to have non-pathological RoM for the tested exercises; the facility performs functional movement screen (FMS) for each athlete at the date of the sign-up to identify deficiencies in RoM [187]. The subjects’ age, gender, and experience level (“novice”, “proficient”, “expert”) were all recorded. Male athletes used a 20kg barbell, while female athletes were provided with a 15kg barbell.

9.3.2 Pressure sensor measurement system
A wearable, non-obtrusive sensor system was used that is able to capture dynamic movement and plantar pressure data (fig. 9.3) [65]. The system was validated in prior work where it was shown to provide valid estimations on subjects’ balance performance [39] [69]. The system was comprised of a thin and flexible foot-shaped plastic foil containing 1260 force-sensitive resistors (FSR) (fig. 9.4). A raw sensor sample featured 21 sensing points in the x-direction and 60 sensing points in y-direction (fig. 9.5). It has been validated against commercial plantar-pressure sensing systems [39]. Although the system is able to detect small differences between different shoe models [65], in this study, the sensor foil was glued onto a flat plywood surface for measurements (Fig. 9.4b). In so doing, the impact of differences in shoes or feet sizes of the various subjects could be removed and the data could be acquired without individual bias. For this study, "zero-drop" shoes i.e. shoes with no drop from heels to toe, or only wearing socks was required from all subjects. During the tests, the athletes stood on the foil in socks or in their own ("zero-rise") shoes. The sensor system sampled FSR values and concurrently recorded motion data from an inertial measurement unit (IMU). IMU data consisted of three-dimensional acceleration, rotation rate, and compass values. Accelerometer read-
Figure 9.3: Study Equipment: Barbell with weights (40kg); two sensor systems on plywood for left and right foot; smart phone controlling sensor systems and displaying data.

ings from the IMU were used to segment the data during analysis. At 100Hz, the system calculated the CoP of each foot and stored it locally. In advance of the testing, the pressure measurement system was presented to each subject and all procedures were explained. Firstly, subjects were asked to perform 10 squats without additional weight (air squat, AS), followed by 10 overhead squats (OHS) with the assigned weight, and 10 front squats (FS) with the same weight. Finally, every subject performed 10 deadlifts (DL) (fig. 9.2d). A coach of the facility supervised the correct execution of the exercises. After a 10 minute rest, each subject was then randomly assigned to perform the warm-up routines (WR), the stretching routines (SR) or simply to further wait (control, CTR). Stretching exercises combined dynamic stretching routines [183], self-myofascial release (SMR) techniques [97], and proprioceptive neuromuscular facilitation [98] (fig. 9.6b). The warm-up routines consisted of a combination of exercises commonly used in the functional training facility (fig. 9.6a). The subjects were asked not to go into exhaustion during warm-up. The CTR group was asked to wait 10 minutes sitting or standing. After the 10 minutes, each exercise was recorded once again. Between exercises, the subjects performed several steps to pick-up the barbell or to readjust stance etc. The move-
ments were visible in the force data and also in accelerometer data. All data were analysed using the Matlab software (R213b, MathWorks, Natick, MA). IMU and pressure data were segmented into episodes of AS, OHS, FS, and DL. Data intervals were labelled with the appropriate exercises. If an athlete performed unexpected movements during data acquisition, the sample was annotated to avoid false labels. For each interval of AS, OHS, FS, and DL, the algorithms extracted the features from pressure data. Since every subject had a different baseline level of mobility, and because feet sizes were different, all data were normalised to feet sizes. Here, in a pre-processing step, the region of interest for each data sample was extracted, i.e. the parts of the insole where the feet were standing and CoP coordinates were mapped to a common range ([0,1]). For both feet, the centre of pressure was extracted: CoPL and CoPR. The left and the right CoP were then combined into a single CoP for the whole body. We calculated the following features from CoP: mean, and the coefficient of variance (CV). All features were calculated on both dimensions, i.e. x and y (fig. 9.5), in a 300ms sliding window with 50% overlap. CV was calculated as the fraction of the standard deviation from the mean value of the sample, i.e. $CV = \sigma / \mu$. This feature reflected how dispersed or scattered the CoP was for a given exercise, as a proxy for stability in balancing exercises. For exercises that required limited balancing
Figure 9.5: Force-data illustrations: clearly visible the different levels of flexibility of the two individuals. The subject on the right has a reduced area of the feet to be used for the exercise. Both images show left feet.
(e.g. DL), the CV feature was used as a surrogate for the regions of each subject’s feet that were used to generate a reaction force. These features have been demonstrated to be valid indicators for balance, stability and body-weight distribution [69].

Prior to addressing the hypotheses, the samples from all groups (pre-stretching/warm-up/control) were tested by ANOVA to examine whether statistically significant differences in the data sets were present. Based on all features, a three-factor analysis of variance (ANOVA, \( \alpha = 0.05 \), factors = [age, gender, exp.]) was performed to work out if age, experience or gender had a measurable effect on the data.

To answer the three questions listed in the first section, repeated two-factor ANOVA (\( \alpha = 0.05 \), factors = [group{WR,SR,CTR}, condition{pre,post}]) was used to detect statistically significant differences between pre- and post-routine data and to answer the three questions.

9.4 Results

ANOVA did not reveal any significant differences in the CoP dynamics between any groups prior to stretching or warming-up. Video analysis showed that some individuals had superior flexibility than most
of the others (fig. 9.1). The control group (CTR) showed no significant changes between the first and the second tests (table 9.1 and table 9.2). The stretching routines affected the CoP for all exercises (table 9.1 and table 9.2). For AS, the mean CoP coordinates shifted approximately 11mm towards the toes. For the OHS (20.5mm; \( p < 0.01 \)), FS (55.5mm; \( p < 0.01 \)) and DL (8mm; \( p < 0.01 \)) exercises, the mean CoP shifted towards the heels (table 9.1). The coefficient of variation (CV) was also affected for all exercises by the stretching protocol. For AS and OHS the CV value decreased significantly (10.2% to 7.0%, and 9.8% to 7.8%, resp.), for FS and DL it increased (9.2% to 14.8% and 4.8% to 7.9%) (table 9.2).

The warm-up routines affected AS and FS significantly on all features (table 9.1 and table 9.2). WR did not affect the OHS, and only weakly (\( p < 0.05 \)) affected the CoP dynamics for DL. After warm-up, the mean CoP during AS shifted 10mm towards the heels. For the FS exercise, the mean CoP was shifted approx. 19mm towards the heels. The mean CoP for OHS remained unaltered (change of approx. 1mm) and the effect on DL (approx. 5mm) was only weakly significant (\( p < 0.05 \)). For the AS exercise, the CV increased from 7.1% to 10.1%, for the FS exercise it increased from 5.0% to 11.5% and for DL, CV increased from 4.1% to 8.0%. CV was not affected significantly by WR for the OHS exercise. The differences in post-routine performances were significant for all exercises for the mean feature. The differences in the CV feature were only significant for AS and FS exercises, but not for OHS and DL.

### 9.5 Discussion

Warm-up and stretching routines affect dynamic and static properties of the CoP during weight-lifting activities. However, stretching seems
Table 9.2: Development of the CV feature in the three groups. The values represent insole coordinates ($1 = 5\text{mm}$) and are presented as (pre / post) routine. Significant differences ($p < 0.01$) are denoted with an asterisk (*).

<table>
<thead>
<tr>
<th>Exercise</th>
<th>CTR</th>
<th>SR</th>
<th>WR</th>
</tr>
</thead>
<tbody>
<tr>
<td>AS</td>
<td>9.6/10.6</td>
<td>10.2/7.0*</td>
<td>7.07/10.1*</td>
</tr>
<tr>
<td>OHS</td>
<td>16.2/14.6</td>
<td>9.8/7.8*</td>
<td>8.7/7.8</td>
</tr>
<tr>
<td>FS</td>
<td>11.9/9.6</td>
<td>9.2/14.8*</td>
<td>5.0/11.5*</td>
</tr>
<tr>
<td>DL</td>
<td>8.2/7.7</td>
<td>4.8/7.9*</td>
<td>4.1/7.8*</td>
</tr>
</tbody>
</table>

to increase stability in complex exercises (OHS) while warm-up does not affect these exercises. In other exercises, the effects of warm-up and stretching are comparable in terms of affecting CV and mean. As there was no effect present from the exercises alone, the detected changes in the WR and SR groups were likely to be caused by warm-up or stretching respectively.

The data from our study suggest that stretching plays a significant role on features of CoP. Common guidelines received by athletes from coaches are to try to keep the major portion of their body weight on the heels during the presented movements [188]. After stretching, the athletes were able to shift their mean CoP closer to the heels for OHS, FS and DL, but not for the AS exercise. While the reason for the shift in CoP towards the toes for the AS is unclear, it is possible that the change resulted from the SR athletes performing the second set of AS faster than the first (as confirmed by video footage). We did not control the speed at the time of the data acquisition. One possible reason is that AS performed rapidly might resemble a jump regarding muscle activation, i.e. AS became more quadriceps-driven. However, it is clear that this effect should be investigated in a different study.

The OHS exercise became more stable after the stretching exercises compared to pre-stretching (decreased CV). In combination with the mean CoP shifting to the heels, we believe that this was caused by a more upright posture that enabled the athletes to maintain the centre-of-mass (of the barbell) farther back and thus did not have to "fight" against the weight [189]. The OHS was the most challenging exercise in terms of flexibility, stability and balance. Thus an improvement in stability and balance is a strong positive result for stretching. Post-stretch, the athletes became less stable during the FS exercises, as indicated by an increased CV value. We believe that this is caused by an increased flexibility in muscles e.g. triceps, possibly limiting a
proper technique in the front squat, while still presenting restrictions in other MTUs, e.g. the hip flexors. This would allow the athletes to maintain the mean CoP closer to the heels during the major part of the move, but it would pull them forward, at, e.g., the bottom of the squat. This hypothesis should be investigated in future studies. An analogous reasoning could explain the increased CV value during the DL exercises.

Regarding question 2: WR significantly affected CoP features during AS, FS and DL, but not during OHS (see table 9.1 and table 9.2). For AS and FS exercise, there was a significant shift of the mean CoP to the heels. This shift might have been caused by multiple factors, for example adapted muscle activation or flexibility changes of, e.g., Achilles and hip flexors (AS) and additionally triceps (important for FS). We don’t think that a practice effect or muscle fatigue are a valid explanation for the observed shift, as the barbell weights used were light for all athletes and the exercises were simple and not new to the athletes. There was no significant shift of the mean CoP during OHS or DL. The overhead squat exercise did not benefit from WR, regarding CV. The CV increased between pre- and post WR during AS, FS and DL. This could be caused by decreased stability or by increased recruitment of plantar area. Because there was no significant increase in CV between pre- and post-testing of the OHS, an increase in plantar area recruitment is more likely. The OHS exercise is the most challenging regarding stability and balance, thus, if WR reduced stability we would have expected to find this effect also (especially) in the analysis of OHS. However, the CV feature for the OHS exercise was not affected significantly, and a trend towards increased stability was observed.

Question 3 was more difficult to answer. There were statistically significant differences in most features after post-routine analyses between the stretching group and the warm-up group. The difference of the impact of both routines was significant for the feature mean during all exercises. The CV feature showed a statistically significant differences between the routines only for exercises AS and FS. Due to considerations regarding air squat presented above (i.e. possible change in speed), we refrain from interpreting the impact of both routines on AS. For the other three exercises, we derived that the impact of the stretching routines were significantly different from the warm-up routine regarding mean CoP. Relative changes of the mean feature from pre-intervention to post-intervention data are larger in the stretching group.
9.6 Conclusions

We compared stretching routines with warm-up routines regarding their effects on CoP of four weight-lifting exercises. A plantar-pressure sensor system recorded data that was later analysed on a computer. Dynamics of the centre-of-pressure were used as a proxy for centre-of-mass dynamics. By analysing changes in CoP/COM dynamics, changes in stability, balance and COM distribution in the subjects were detected. Both strategies affected features of CoP: mean centre of pressure values shifted to the heels during OHS and FS, which could indicate a more upright body posture. The changes in mean CoP during AS were contradicting, but we assume that the increased speed at which the stretching group performed the AS in the second set was causing those subjects to shift their weight to their toes rather than to the heels. The warm-up routines did not cause a statistically significant effect for the OHS exercise, whereas the stretching routines did. Stretching seemed to be beneficial regarding stability, as the CV decreased significantly between pre- and post-stretching testing during the most difficult exercise, the overhead squat. A comparison of the effects of both routines was difficult and due to the aforementioned

9.5.1 Limitations

A large variability in baseline flexibility could introduce an unknown bias to the analysis. There were two athletes with an exceptionally good but an much lower overall flexibility. However, the reduced flexibility was still not considered pathological as assessed by the FMS tests. In the squat position, the flexible athlete was able to maintain an angle between the floor and his back of approx. 65 deg. The non-flexible athlete, however, achieved a maximal angle of 35 degrees. In future studies, the subjects should be assessed regarding their baseline flexibility and mobility prior to group assignments. Established systems exist to categorize the flexibility of athletes [190,187], and these could be easily employed to enhance the quality of the data. Also the number of participants should be increased, especially if pre-screening is applied. In addition, all subjects should be monitored during the intervention: we suspected some participants of the warm-up group worked at a too high an intensity and therefore their post-intervention results (e.g. AS speed) were possibly biased. Here, video-analysis or motion capture could deliver data on the RoM of specific joints.
bias by speed etc. during AS. We don’t think that a reliable statement could be made about which routine is more advantageous for athlete’s balance/stability performance in AS. However, we think that there is evidence of an advantageous effect on stability of stretching, as the improvements in CV during OHS were significant.

9.6.1 Outlook

A follow-up study should focus on one distinctive exercise. We propose to address OHS due to the requirements on balance/stability or FS due to its relatively low complexity, but significant requirements on lower-body flexibility. Furthermore, a focused view of one item in the kinematic chain, e.g. the ankle joint, seems to be appropriate due to the fact that ankle flexibility seems to be the most limiting factor for most athletes. Another interesting question is the role of the bar weight. It would be interesting how the balance/stability performance changes with increasing weight. The used sensor system could also be applied as a training tool. CoP data can be visualized on a tablet or smartphone and displayed to an athlete in real time. A subject then could directly alter her body posture for a more optimal position.
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>ADC</td>
<td>Analog to Digital Converter (12, 20)</td>
</tr>
<tr>
<td>ADL</td>
<td>Activities of Daily Living (3, 4)</td>
</tr>
<tr>
<td>ANOVA</td>
<td>ANalysis Of VAriance (31)</td>
</tr>
<tr>
<td>ANT+</td>
<td>A proprietary open access multicast wireless sensor network technology by Dynastream (55)</td>
</tr>
<tr>
<td>API</td>
<td>Application Programming Interfaces (11)</td>
</tr>
<tr>
<td>BFT</td>
<td>Bewegungs-Funktions-Test (4)</td>
</tr>
<tr>
<td>BLE</td>
<td>Bluetooth Low Energy (48)</td>
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<tr>
<td>BPPV</td>
<td>Benign Paroxysmal Positional Vertigo (ix, xi, 14, 15, 35, 36, 37, 47, 49, 107)</td>
</tr>
<tr>
<td>COM</td>
<td>Center Of Mass (6, 7)</td>
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<td>COP</td>
<td>Cente Of Pressure (ix, xii, 7, 9, 12, 20, 28, 32, 33, 34, 38, 45, 46, 47, 48)</td>
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<td>CP</td>
<td>Cerebral Palsy (9)</td>
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<tr>
<td>CS</td>
<td>Compressive Sampling (25, 28)</td>
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<td>FFT</td>
<td>Fast Fourier Transform (8)</td>
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<tr>
<td>FGA</td>
<td>Functional Gait Assessment (ix, xi, 12, 32, 34, 102)</td>
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<tr>
<td>FSR</td>
<td>Force Sensitive Resistors (20, 23, 24, 33)</td>
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<td>GRF</td>
<td>Ground-Reaction Forces (7)</td>
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<tr>
<td>I^2C</td>
<td>Interegrated Circuit (12, 20, 22, 24, 28, 47, 48, 56, 58, 59, 70, 71)</td>
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<td>IC</td>
<td>Integrated Circuit (20)</td>
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<tr>
<td>IMU</td>
<td>Inertial Measurement Unit (ix, xii, 2, 3, 5, 6, 8, 9, 11, 12, 14, 15, 20, 22, 24, 28, 29, 30, 31, 32, 39, 40, 43, 46, 47, 58, 79, 129)</td>
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<td>Overhead Squat (44, 46)</td>
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<tr>
<td>OMCS</td>
<td>Optical Motion Capture Systems (5, 6, 9)</td>
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<td>PD</td>
<td>Parkinson's Disease (8)</td>
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<td>Pressure-sensing IMU (12, 14, 15, 20, 23, 24, 28, 32, 34, 35, 38, 40, 47)</td>
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<td>Serial Peripheral Interface (56)</td>
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<td>Support Vector Machine (9, 34, 41)</td>
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<tr>
<td>TUG</td>
<td>Timed-Up-and-Go (4, 11, 20, 29)</td>
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Curriculum Vitae

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