Analysis of short term path prediction of human locomotion for augmented and virtual reality applications

Analysis of Short Term Path Prediction of Human Locomotion for Augmented and Virtual Reality Applications

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Abstract—**When human locomotion is used to interact with virtual or augmented environments, the system's immersion could be improved by providing reliable information about the user's walking intention. Such a prediction can be derived from tracking data to determine the future walking direction.**

This paper analyses how tracking data relates to navigation decisions from an egocentric view in order to achieve a reliable and stable path prediction. Since tracking data is noisy, a smoothening is required that eliminates oscillations while still recognizing trends in human locomotion. Thus, we analyze different approaches for path prediction, determine relevant setting values, and verify the results by a user study.

Results indicate that robust short term prediction of human locomotion is possible but care must be taken when designing such a predictor.

Keywords-**prediction; human path prediction; head tracking; walking direction; facing direction; virtual reality; augmented reality; exponential smoothing**

I. Introduction

Walking or human locomotion is our most intuitive way of navigating in the real world and an important human perception entity to gain information about objects' sizes and distances to each other, and for the orientation in our environment. In order to further increase immersion of virtual environments, this real walking experience should be integrated in a way that goes far beyond today's treadmills or walking-in-place installations. Such new systems should be non-obtrusive and should not hinder the user to perform tasks in a virtual environment. However, constructing such systems is still a challenging task, since it requires to measure a user's position, and also to make correct assumptions about his future actions in the environment.

Today's smart mobile phones for instance can help the user to find destinations by using GPS data and mapping services. But in order to perceive the information from the mobile, the user has to interrupt his main activity to retrieve or to enter information. Such systems - as well as those being used in a virtual environment - only offer information related to the current position of the user and thus to his current action. Today's systems only have little intelligence in determining the user's intention and in making the correct suggestions.

Hence, it is crucial to improve such systems by making them know what a user is doing or is planning to do. Having such information about the user's intention would make virtual environments more responsive, and also more intelligent. In order to provide information at the right time some sort of prediction is required. Head-up displays for instance, which are used in augmented reality (AR) systems, might provide the user with information about the environment while he continues some other activity. When entering a train station for example, a train schedule could be shown to the user; or when walking down a hallway towards a shop that just closed, the system could inform the user before he reaches the closed door.

When providing real walking in virtual environments where the virtual environment is larger than the tracked space, path predicition is essential. In this so-called redirected walking, a virtual room is compressed into a physically smaller room by guiding the user on a curved or scaled path [1]–[3]. Since the visual perception overrides the haptic sensation of walking, the user does not notice this compression. However, in order to plan ahead such redirections of the user, it is required to integrate path prediction.

One approach to determine what a person plans to do when walking in a real or virtual environment is to use position and orientation tracking data. Such sensors are often already integrated in mobile phones (e.g. accelerometers, gyroscopes and GPS). By using advanced sensor fusion algorithms, such sensor information can be combined to provide continuous position and orientation tracking data [4]. Since orientation and acceleration tracking devices can be designed with a very small form factor, they can easily be integrated into head-up displays or attached to other AR glasses [5], [6]. However, when providing real walking in virtual environments, such sensors usually have to be attached to the visual output device, i.e. to the head-mounted display (HMD) or to other glasses.

Having position and orientation data of a person's head,

the challenge is to make some feasible prediction of the future path, in particular when the user is allowed to make decisions whether he wants to go left or right at some positions in the environment. In contrast to other literature for predicting pedestrians' movements [7], this paper treats this problem from an egocentric perspective.

Path prediction can be divided into three time intervals. A very short term prediction (milliseconds) of human locomotion is given by different physical constraints of human movement like maximum acceleration etc. A short term prediction (seconds) is given by human way finding and the target a persons wants to reach. Long term path prediction (minutes) is closely related to a person's cognitive map of the environment and the planned destination.

In this paper, we analyze how tracking data relates to navigation or direction decisions for short term prediction of human locomotion. We present an experiment in which participants had to walk through a maze-like environment and had to decide for different directions. An analysis of the recorded user paths shows the problems when trying to make a robust estimation of the future path. Different approaches for path prediction are presented and discussed. Finally, the path data from the experiment is used for a comparison of the proposed approaches.

II. RELATED WORK

Path prediction is especially important when real walking is used as a locomotion interface to navigate in a virtual environment. For instance, Peck et al. propose a real walking locomotion interface where users can visit immersive virtual environments that are larger than the tracked space [8]. They make use of the fact the vision usually dominates the proprioceptive sensation and thus imperceptibly rotate the virtual environment around the user [9]. Hence, the user is kept inside the borders of the tracked space. In order to plan such redirections, it is crucial to know the user's future path.

Nitzsche et al. proposed a similar locomotion interface and suggested two path prediction approaches [2]. A non-target based approach simply uses the user's current facing direction (i.e. the head orientation) as future walking direction. For an environment, in which targets can be identified, a more sophisticated approach is suggested. Weight coefficients are assigned to all targets or potential goals. The coefficients of all targets in the field of view are increased while a user is looking at them or decreased otherwise. The target with the highest weight defines the predicted direction. Another approach is to use linear extrapolation of the user's previous path [10].

Interrante et al. suggest to use a hybrid approach [11]. While a person is walking, the average direction of motion over the past n seconds is used as prediction. Whenever a person is not moving the facing direction is used. As soon as person starts moving, the influence of the facing direction on the prediction is decreased and the influence of the walking

direction is increased. Steinicke et al. proposed another hybrid approach [3]. The walking direction is used for the prediction and the facing direction is used for verification. The walking direction is considered as prediction if the angle between walking and facing direction is smaller than 45 degrees, otherwise no reliable prediction is assumed.

Above publications present different approaches for path prediction in virtual reality (VR), but lack evaluation or comparison of the proposed methods.

In the research field of human robot interaction, recognizing a person's intended action using motion prediction is of great interest. In this case, the movement prediction is primarily used to classify interactions with the robot and thus is regarded from a exocentric perspective [12].

In the research area of urban planning and transportation science, the movement patterns of pedestrians are analyzed [13]. These models are usually used for large scale simulations of pedestrian flow.

Different tracking systems for pedestrian tracking have been proposed - e.g. using shoe-mounted inertial sensors [14] or ultrasound-aided systems [15]. These systems focus on providing a stable and accurate estimation of the user's position. Usually a Kalman Filter (KF) is used for the estimation, which also allows providing some sort of predictive tracking. For instance, Kiruluta et al. present a method for predictive head movement tracking [16] using a KF. Similarly, LaViola shows that double exponential smoothing can be used for predictive tracking [17]. A comparison of prediction and filtering methods is given in [18].

Such predictive tracking algorithms usually have prediction times of several milliseconds up to one second in order to compensate for system latencies. They employ a movement model and noise model that fit such short prediction times (e.g. 100ms in [17]). In contrast to this, our goal is not to make a robust estimation of the head position but a robust prediction of the *intended* walking direction. Ideally, this prediction should hold for several seconds rather than milliseconds.

III. PATH PREDICITON FROM TRACKING DATA

A tracking system that is carried by a person typically provides position and orientation data at discrete time steps. Assuming a decent update rate, the current speed and acceleration can be estimated by approximating the derivative from the discrete time samples.

In order to make a prediction of the future direction of movement, we can interpret and extrapolate this tracking data in different ways presented below.

It makes sense to limit the path prediction problem to the actual walking plane (2 dimensions for position, orientation as rotation around the normal of the walking plane). This implies that the position and orientation data is projected on the walking plane. The position data at time t is referred to

as $\vec{x}_t$ where $\vec{x}$ denotes the 2-dimensional position vector and t is the discrete time index starting at time 0.

A. Facing Direction

If the orientation sensor of the tracking system is attached to a person's head, it can track the facing orientation. We can express the facing orientation as a 2-dimensional direction vector in the reference frame of the tracking system projected on to the walking plane. The normalized facing direction vector is denoted by $\vec{f}$.

The current facing direction can be directly interpreted as a prediction of a person's intended direction of movement. Especially when the person is not moving, i.e. the recorded position data is constant, orientation data is the only prediction information.

In case targets are known in an environment, $\vec{f}$ can serve as a prediction by choosing the target at position $\vec{p}$ that has the smallest angular deviation from the current facing direction $\vec{f}_t$. The angle between a target and the facing direction can be calculated using the scalar product:

$$\theta = arccos\left(\frac{\vec{f}_t \cdot (\vec{p} - \vec{x}_t)}{|\vec{f}_t||(\vec{p} - \vec{x}_t)|}\right) \tag{1}$$

The major problem of using the facing direction for prediction is that it does not necessarily represent a person's gaze direction. For this, an eye tracker would be required. When looking at a target, humans often only move their eyes instead of their complete head. Hence, especially if two targets are close to each other, the facing direction is a critical predictor.

B. Walking Direction and Speed

The change of the position $\vec{x}$ over time provides information about a person's current and past movement. Thus, the displacement vector $\vec{w}_t$, defined by

$$\vec{w}_t = \vec{x}_t - \vec{x}_{t-1} \tag{2}$$

gives the direction of movement from time t-1 to t. Given a constant sampling interval τ, the current speed is given by $|\vec{w}_t|/\tau$.

If we assume no information about an environment, it is plausible to postulate that humans walk to a target in a straight line, as a matter of energy minimization. Therefore, the current walking direction is an intuitive prediction of the future path.

As for the facing direction above, $\vec{w}$ can be used to determine the chosen target in an environment using the angular deviation.

When a person is not moving, $\vec{w}$ is zero and no prediction can be made. The displacement vector must be used carefully as a predictor when the movement is slow. I.e. if $|\vec{w}|$ is of the same or smaller magnitude as the tracking system's noise, the predictions will be wrong. Thus, a lower bound for $|\vec{w}|$ must be chosen depending on the characteristics of the tracking system (update rate, noise, etc.).

C. Smoothing and Robustness

Tracking data is usually noisy. Therefore, some smoothing of the data is required to reduce the effect of noise on the path prediction. Noise will make the prediction unstable. Additionally, the movement of the body during walking is not perfectly aligned with the intended walking direction. If the tracking system is mounted on a person's head, it will also move sideways and up and down due to the mechanics of human gait. Hence, if we want to determine the intended walking direction we have to reduce the effect of gait oscillations on the path prediction.

Next, different approaches for smoothing data are presented. These smoothers could be applied to the $\vec{f}_t$ or the $\vec{w}_t$ vectors. But as discussed in Section V, smoothing is especially important for the walking direction. Hence, the equations are presented for the $\vec{w}_t$ vectors. $\vec{s}_t$ denotes the smoothed path prediction at time t.

1) Unweighted Moving Average: One of the simplest methods to smooth data is the moving average method given by

$$\vec{s}_t = \frac{1}{k}\sum_{i=0}^{k-1}\vec{w}_{t-i} \tag{3}$$

k represents the time horizon over which the arithmetic mean is built. Hence, this means that $\vec{s}_t$ is the average displacement of the past k time steps.

The major problem of the unweighted moving average is that at least k samples must be recorded before a prediction can be made. Another problem is given by the fact that the $\vec{w}_t$ are displacement vectors. Hence the moving average rewritten using (2), reduces to

$$\vec{s}_t = \frac{1}{k}\sum_{i=0}^{k-1}(\vec{x}_{t-i} - \vec{x}_{t-i-1}) = \frac{1}{k}(\vec{x}_t - \vec{x}_{t-k}) \tag{4}$$

This means that all position samples between time t-1 and t-k+1 are actually ignored for the smoothing. If the time horizon k is not chosen carefully, the prediction will be unstable e.g. due to gait oscillations.

2) Exponential Smoothing: The simple moving average smoother gives the same weight to all k past measurements. In contrast to this, exponential smoothing weighs past measurements with an exponentially decaying factor:

$$\vec{s}_0 = \vec{w}_0 \tag{5}$$
$$\vec{s}_t = \alpha\vec{w}_t + (1 - \alpha)\vec{s}_{t-1} \tag{6}$$

$\vec{s}_t$ can be rewritten as

$$\vec{s}_t = \alpha\vec{w}_t + \alpha\sum_{i=1}^{t-1}(1 - \alpha)^i\vec{w}_{t-i} + (1 - \alpha)^t\vec{w}_0 \tag{7}$$

Exponential smoothing includes all past measurements into the current prediction. The smoothing is controlled with the factor $\alpha \in (0, 1)$. If α is close to 1, the smoothing effect

is low and new measurements are weighted higher. If α is close to 0, the level of smoothing is higher.

The difficulty in exponential smoothing lies in the correct choosing of α. If it is too high, noise and gait oscillations will influence the prediction. If it is too low, real changes in the walk direction might be detected too late. In order to give a mathematical basis for estimating α, the following limit case can be regarded. Assume that the measurement v has been constant at some value v_o and the smoothed value has been stable at $s_o = v_o$. Now at time t-k the measurement input changes to a new constant value v_n. We want to know how many time steps k it will take until s_t reaches factor q of the new measurement value v_n. Hence s_t can be rewritten as

$$\alpha v_n + \alpha v_n \sum_{i=1}^{k} (1-\alpha)^i + \alpha v_o \sum_{i=k+1}^{t-1} (1-\alpha)^i + (1-\alpha)^t v_o \tag{8}$$

Now the factor of change from the old to the new measurement is given as

$$q = \frac{s_t - v_0}{v_n - v_o} \tag{9}$$

$$= 1 - (1-\alpha)^{k+1} \tag{10}$$

$$\alpha = 1 - (1-q)^{1/k+1} \tag{11}$$

Using the equations for the summation of geometric series on (8) and inserting in (9) gives an equation for determining α. For instance, if the smoother is to follow a step function to 80% ($q = 0.8$) within the next $k = 180$ measuring time steps, α should be about 0.009.

3) Double Exponential Smoothing: Exponential smoothing can be improved if there is a trend in the data like the change of the walking direction. This so-called double exponential smoothing is given by

$$\vec{s}_0 = \vec{w}_0 \tag{12}$$

$$\vec{s}_t = \alpha \vec{w}_t + (1-\alpha)(\vec{s}_{t-1} + \vec{b}_{t-1}) \tag{13}$$

$$\vec{b}_t = \beta(\vec{s}_t - \vec{s}_{t-1}) + (1-\beta)\vec{b}_{t-1} \tag{14}$$

The $\vec{b}_t$ vectors represent the current trend in the data. α is the data smoothing factor as for normal exponential smoothing. $\beta \in (0,1)$ is the so-called trend smoothing factor. It controls how much the current trend is influenced by the change in the smoothed prediction output over time. $\vec{b}_0$ defines the initial trend in the data.

By looking at the definition of $\vec{w}_t$ in (2), we see that $\vec{w}_0$ is not defined by the data. Thus in order to use the smoothing methods, prediction actually has to start at time t=1.

Another solution is to give $\vec{w}_0$ a suitable initial value. For path prediction with double exponential smoothing, the following approach is suggested. Assuming that a person starts to move at time t=0, set $\vec{w}_0 = c\vec{f}_0$ using the facing direction at time 0 (similar to [11]). Under the assumption
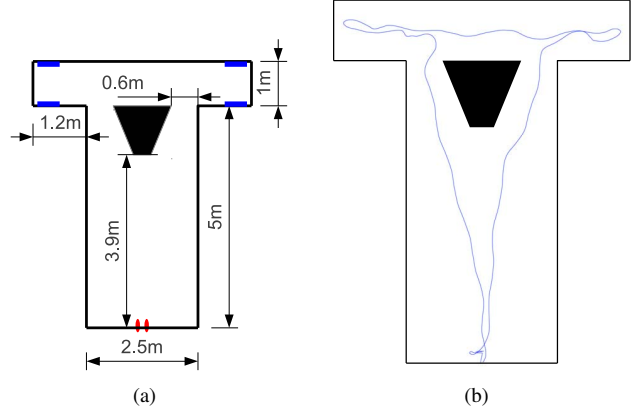

Figure 1. (a) The symmetric T-maze for the experiment. Walls are in black, two red ellipses show the start and end position, the four blue bars mark the position of the calendar pictures. (b) Shows a typical walk path through the maze during the study.

that the initial facing direction is the most likely direction of movement, we can set the initial trend to $\vec{b}_0 = (0,0)$. The magnitude of $\vec{w}_0$ influences how much impact it has on the smoothed output. Therefore the constant c should be chosen so that it reflects a reasonable speed. E.g. c could be defined using the human average walk speed $\bar{v}$ and the given update rate r as $c = \bar{v}/r$.

IV. EXPERIMENT

A study was conducted where participants had to walk inside a simple maze-like environment. Different paths through the maze were available so that participants were forced to make a choice. During walking, a head-mounted tracking system was used to record the path. The goal of the study was to allow the analysis of head position and orientation data and especially how the choice of a target or direction relates to the recorded data.

A real, physical maze environment was constructed deliberately instead of a virtual environment. Even though the hardware allows visiting a virtual scene by real walking, the limited field of view (FOV) of the head mounted display (HMD) and simulator latency might influence the results of the study.

A. Experimental Setup

In a 5m x 7m room, movable walls were installed to form a 'T' shaped maze. Figure 1 shows the design and dimensions of the maze. An obstacle in the center of the maze forced subjects to walk left or right. Four calendar pictures were placed at both ends of the maze (see Figure 1). The maze was designed to be perfectly symmetric (left, right) and no distractions were present except for the calendar pictures. The pictures were not visible during the decision phase whether to move left or right. The start

Figure 2. Picture of the study setup. A subject wears the backpack with the notebook and the HMD with the tracking system. The red paper in the middle is the center mark for the initial calibration.

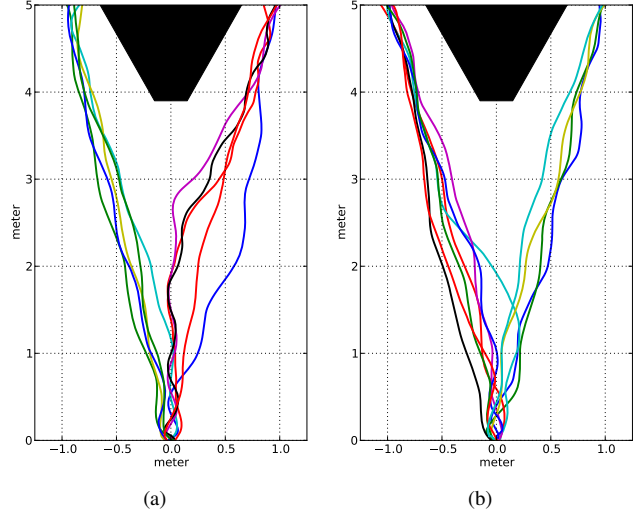
(a)   (b)

Figure 3. Paths recorded during the experiment. Only the lower part of the T-maze is shown, i.e. until the participants had decided for left or right. (a) Shows the paths recorded during the EX condition and (b) during the CO condition.

position was placed in the center of the lower end of the maze.

The ceiling of the whole room is equipped with paper markers for the Intersense IS-1200 tracking system [19]. The IS-1200 system is an inside-out tracking system that can easily be attached to an HMD. It tracks position and orientation (6 degrees of freedom) at an update rate of 180 Hz. In order to track a subject wirelessly in the maze, a backpack-mounted notebook was used to record the tracking data. The tracking system was attached to a Triviso Scout HMD. The HMD was only used to mount the tracking system properly on a subject's head. Figure 2 shows a photo of the maze environment and a user wearing the notebook and the tracking system.

B. Participants

In total, 11 participants took part in the experiment (7 male and 4 female, median age 31). Participants were recruited from the institute and included students, senior researchers and administrative staff. All participants were unaware of the purpose of the study.

C. Tasks and Conditions

In order to evaluate the choice of a path in a known and unknown environment, the study was conducted under two conditions.

1) Explore Condition (EX): In the first task, all subjects were new to the environment and had no information about the maze. They were told to walk through all corridors of the maze and to return to the start position.

2) Count Task Condition (CO): At the ends of the T-maze, calendar pictures with dates were presented (see Figure 1). The second task was to count the total number of Sundays on all 4 calendar pictures and return to the start position. In this condition, all participants already knew the maze and where to find the targets.

D. Procedure

All subjects received oral explanations about the task and procedure. At the beginning of the study, the participants mounted the HMD and backpack in a different room and were guided blindfolded to the start position. Subjects had to place themselves properly at the start position and were instructed to look 4 seconds at the center mark (see Figure 2) before starting the task. This served as an initial calibration of the facing direction. Task 2 (CO condition) was explained to them after they finished the first task (EX condition).

V. RESULTS AND DISCUSSION

In total, 10 out of 11 participants correctly finished the tasks of the experiment. One participant did not properly finish the task in the EX condition but could participate again in the CO condition. Hence, 10 correct paths were recorded during the explore task condition (EX) and 11 during the count task condition (CO).

In the following, the analysis of the path data is limited to the first 4 m from the start position towards the obstacle, see Figure 1. We refer to this axis as the y-axis and indicate position with a y-value in meters starting from 0 at the start position. Within this "decision area", subjects had to decide whether to go left or right. Moreover, we defined two targets at $y = 5$, "left" and "right", each in the center of the left or right passage around the obstacle. For the evaluation of the path prediction, we use the angular deviation of the prediction from the targets as suggested in Section III-A.

Figure 3 shows all paths recorded during the experiment. Gait oscillations can be easily identified for most paths. The paths indicate that the majority of the subjects decided early,
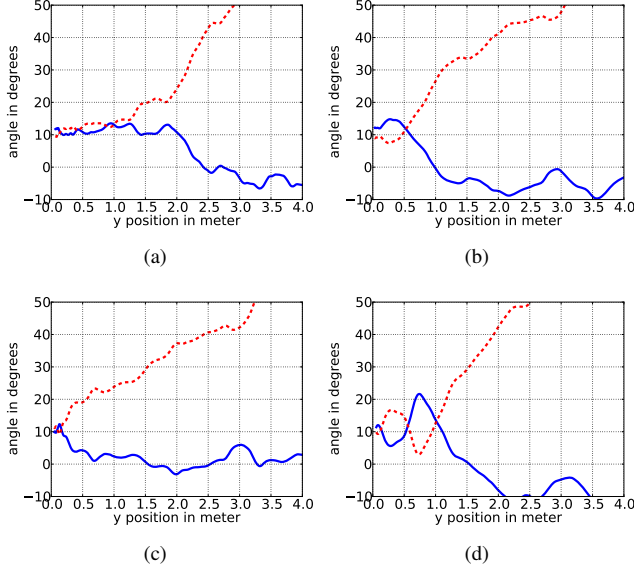
Figure 4. Angular deviation of the facing direction from the two targets while a subject is moving from y=0 to y=4. A solid blue line shows the deviation from the chosen target direction and the dashed red line the deviation from the other target. (a), (b) were recorded during the EX condition and (c), (d) were recorded during the CO condition. The angular deviation is positive for rotations from the targets towards the center of the obstacle.

Figure 5. EX condition: angular deviation of the walking direction from the two targets while a subject is moving from y=0 to y=4. A solid line represents the deviation from the chosen target and a dashed line the deviation from the other target. The grey line is the raw data, red is the exponentially smoothed data and green is the double exponentially smoothed data.

i.e. $y \leq 1$, for left or right. This holds especially for the CO condition where only one of 11 subjects changed the initially chosen direction after $y \approx 1.4$. During the EX condition, three to four of 10 subjects decided later at $y \approx 2.5$. This indicates that if the environment is unknown to a person, path prediction is more difficult.

Within the decision area the average walk speed of all recorded paths in both conditions was 0.95 m/sec, with a standard deviation of 0.22 m/sec.

A. Facing Direction

Figure 4 shows the angular deviation of the facing direction from the targets. The four plots represent four different subjects while they moved from $y = 0$ to $y = 4$. A predictor using the facing direction would thus predict that target which is closer to 0 degree. For instance, in Figure 4(d) the predictor would predict the wrong target for $y \in [0.6, 1]$ and the correct one for $y > 1$.

The data used in Figure 4 is the raw data from the tracking system. There is little noise in the data and the plots represent quite well a subject's head orientation. Hence, smoothing cannot improve the prediction. For example in Figure 4(d) at position $y = 0.7$ the participant deliberately turned his head to look towards the other target.

In general, the facing direction should be used carefully as a predictor. First, it does not necessarily reflect a person's real gaze direction. A person might just move his eyes instead of the whole head. Second, the facing direction
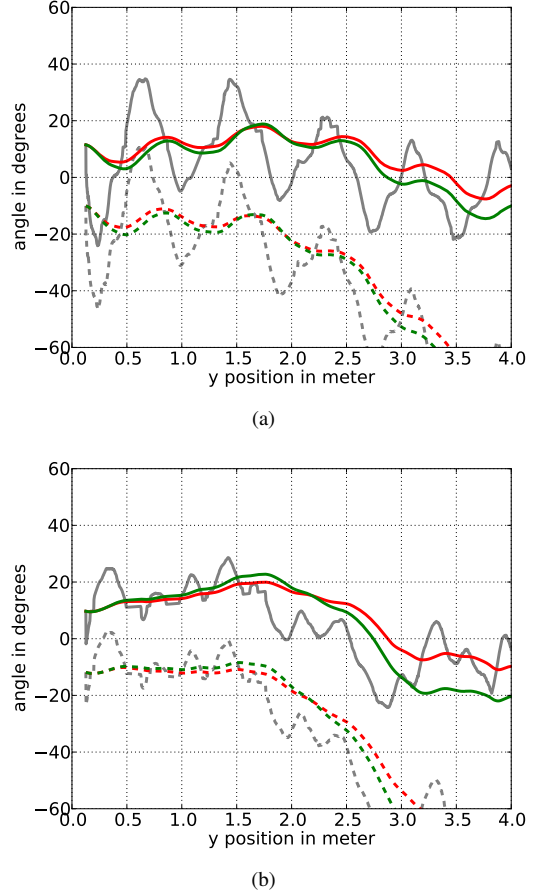
is not necessarily aligned with the walking path. It is highly influenced by visual distractions. This experiment was designed to have no visuals distractions. However, if pictures would have been placed only on one side of the maze, a subject might have looked at them from time to time while walking towards a target. Thus, the average facing direction vector would not point to the chosen target.

An analysis of the initial facing direction, i.e. when a person just starts to walk, is omitted because of the study design, see Section IV-D.

B. Walking Direction and Smoothing

Figure 5 and 6 show the angular deviation of the walking direction from the targets for the EX and CO condition. The four plots represent four different subjects while they moved from $y = 0$ to $y = 4$. The walking direction is calculated as given in Section III-B. The solid lines represent the angular deviation from the chosen target and the dashed
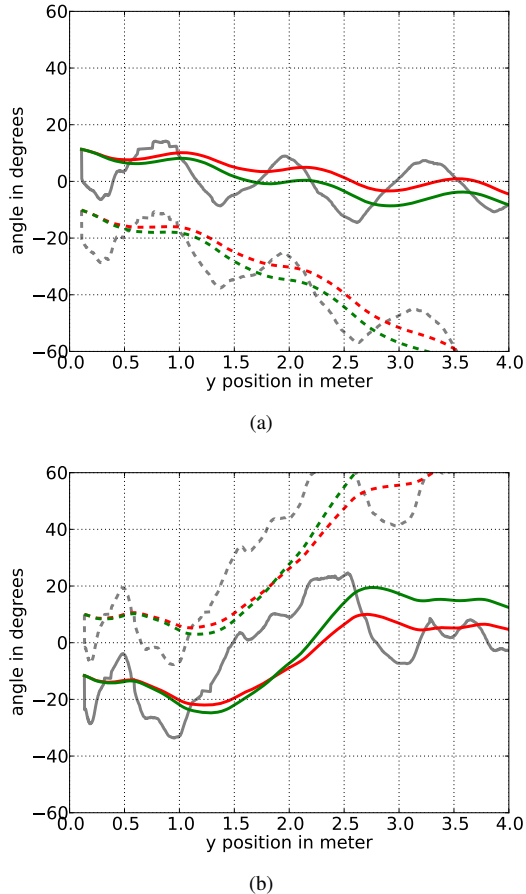
(a)

(b)

Figure 6. CO condition: angular deviation of the walking direction from the two targets while a subject is moving from y=0 to y=4. A solid line represents the deviation from the chosen target and a dashed line the deviation from the other target. The grey line is the raw data, red is the exponentially smoothed data and green is the double exponentially smoothed data.

lines the deviation from the other target. The grey lines show the raw measurement data without any smoothing. Gait oscillations are well visible in all plots. When using the walking direction for prediction, gait oscillations turn out to be the largest disturbance. Hence, smoothing is essential. In Figure 5 and 6 the colored lines represent smoothed values using either exponential or double exponential smoothing. The initial value of $\vec{w}_0$ is chosen as suggested in Section III-C ($\vec{f}_0$ points to the center of the obstacle). Smoothing with moving average turned out to work worse and due to its problems mentioned above, the results are not presented.

As for the facing direction above, a predictor using the walking direction predicts that target which is closer to 0 degree in the plot. In other words, if a dashed line is closer to 0 than its solid counterpart, the wrong target is predicted.

Different parameters for the smoothers were evaluated. For the given experiment, a smoothing factor of $\alpha = 0.004$ (for normal and double exponential smoothing) and a trend

smoothing factor of $\beta = 0.004$ turned out to work best. I.e. they provide a stable prediction but still react reasonably to changes in the intended direction of movement. Using equation 9 from Section III-C and the given update rate of 180 Hz, we can estimate the percentage of change. Hence, one second after a change in the walking direction, roughly 50% of that change will be included into the smoothed walking direction and roughly 75% after two seconds.

Figure 5(a) and (b) show both data from subjects who did not decide right away for a target and first walked roughly straight forward. For instance, as can be seen in Figure 5(b), the double exponential smoother is a bit quicker in detecting the decision and outruns the exponential smoother at $y \approx 2.2$. Figure 6(b) is the extreme case where a participant changed his decision and turned around (see also Figure 3). Similarly, the double exponential smoother is faster in detecting this change. Figure 6(a) shows a typical plot of a subject who walked straight to the chosen target. In such cases, both smoothers provide reliable and robust predictions.

VI. CONCLUSION AND FUTURE WORK

In this paper we have shown how short term path prediction of human locomotion can be realized by using tracking data. One quickly comes up with the idea of using some sort of extrapolation of the tracking data. As shown in this paper, the problem must be treated carefully more in detail. It is crucial how such an prediction is done and what information is extracted from the tracking data. The dynamics of human locomotion are different for different persons, e.g. because of different step lengths, and make it difficult to find a robust generic predictor. Predicting the future path using double exponential smoothing of the walking direction turns out to work well as a predictor while a person is walking. When a person just starts to walk, the facing direction can be used as an initialization value for the smoother.

Future path prediction approaches might use accelerometer data to detect steps and thus learn the step length from the user. This would allow automatic adaptation to a person and improve the prediction. The displacement of the pelvis during walking could also be explored for improved tracking if it is not possible to attach a sensor to a person's head [20].

Using the facing direction for prediction is critical when a person moves the eyes only instead of the head. This happens especially if several targets are close to each other. Hence, eye trackers could be used to correctly identify the user's gaze direction.

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