Estimation of the Average Gait Velocity based on Statistical Stride Parameters of Foot Sensor Data

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Abstract: The paper deals with the estimation of gait parameters based on data acquired by inertial measurement units (IMU) placed at the middle foot (metatarsus). The developed method described in (Loose and Orlowski, 2015) is robust against a wide spectrum of the gait speed. The gait parameters (stride duration, length, velocity, distance) are calculated stride by stride with excellent quality. This paper is focused on experimental data acquired during walking on treadmill with a speed profile. First the robustness of the method is shown and quantified using statistical characteristics of each speed level and the whole walking distance. Second the determined speed profiles are evaluated against the adjusted speed profile and an alternative camera based measurement. Third the influence of the walking speed on various physical and statistical stride parameters is discussed. Fourth a model to estimate the walking speed as a function of the root mean square of the magnitude of the angular velocity vector is proposed and evaluated. The rms is calculated for the acquired sensor data after stride detection for the whole stride. The proposed method is applicable to any IMU applied to the metatarsus.

1 INTRODUCTION

In the middle of the last century Perry (Perry, 2010) and Murray (Murray, 1964) observed, measured and analysed the normal and pathological human gait. In addition to the graphical representation of the normal range of motion Perry published the acquired motion data. The gait pattern covers one stride, the full period of movement of one leg, one stance and one swing phase. The given patterns include motion ranges of joint angles (hip, knee and ankle), the angle between the thigh and the vertical axis (in the sagittal plane).

During the last decade accelerometers, gyrometers as well as integrated inertial measurement units became freely available at the market: from low cost sensors to relatively expensive IMU assembled in small and light weight packages. IMU are integrated in most smartphones. They provide acceleration data, and more and more angular velocity and magnetometer data as well as an estimation of orientation.

In this paper we focus on the estimation of the average gait velocity based on statistical stride parameters of foot sensors. Based on the data of one IMU sensor placed on the metatarsus various gait values and parameters are determined:

- cadence, distance and velocity of motion,
- characteristics of each or averaged stride like initial and terminal point, length, height, width, duration of stride, stance and swing phase.

In addition one-stride statistical parameters like minimum, maximum, mean and root mean square of these characteristics are calculated. The “average” stride is determined after the stride time normalization.

In section II of this paper the used scenarios including the experimental setup, the task for the cohorts and the evaluation software are described. Section III gives an overview about our investigation of walking on treadmill with a speed profile. First the robustness of the method is shown and quantified using statistical characteristics of each speed level and the whole walking distance. Second the determined speed profiles are evaluated against the adjusted speed profile and an alternative camera based measurement. Third the influence of the walking speed on various physical and statistical stride parameters is discussed. Fourth a model to estimate the walking speed from measured one-stride-root mean squares of acceleration and/or

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angular velocity magnitudes is proposed and evaluated. The proposed method is applicable to any IMU applied on the metatarsus. A similar idea is given in (Juen et al., 2014) in the context of health monitoring using mobile phones. Finally we will conclude and give an outlook for further investigations. It is expected that the method can be applied to sensors placed above the ankle or at the trunk. It can also be implemented on smart phones.

2 SYSTEMS AND EXPERIMENTS

For about five years we have been using sensor systems for the acquisition of various motion data. Sensors were applied directly to limbs/body were tested as well as position measurement systems, which are used for comparison in motion data acquisition. Since a couple of years we have focused on human walking, tried to understand the underlying process and to find best positions of sensors. Xsens MTw sensors providing strapped down data including sensor orientation are used. A robust and reliable algorithm which is applicable to a wide range of walking scenarios (~2-8 km/h) was developed. The algorithm was evaluated on data acquired from foot sensors in two main scenarios addressed to a large number of healthy subjects.

2.1 9DOF Xsens MTw Sensors

The 9DOF Xsens MTw sensor incorporates three microelectromechanical sensors: triple-axis gyroscope, accelerometer and magnetometer. Onboard, the data of the primary sensors are sampled at 1800 Hz. Strap-down integration (SDI) is used to estimate the orientation with a transfer rate of 60 Hz (for seven sensors). They are connected via Bluetooth to one Awinda station and the data acquisition software “MT Manager”. All involved sensors are synchronized with high accuracy (< 10 μs). The software provides linear acceleration a, angular velocity ω, magnetic field m and quaternion q. The sensors need calm or slow motion for calibration, to determine the initial orientation of the sensor with respect to the world coordinate system (Roetenberg, Luinge and Slycke, 2009).

2.2 Experimental Setup

The sensors are clipped on body straps attached similarly to the left and right lower limbs and one in the middle of the back. Figure 1 shows two different placements of the sensor on the metatarsus. The distances of the sensors from the floor as well as the length of the limbs are fixed in the experimental record of each subject.

Figure 1: Two placements of foot sensors (on the side – left, on the top of the foot - right).

2.3 Scenario

This paper is focused on human walking on treadmill with a stepping-up speed profile over a time period of 8 minutes and a distance of about 640 meters. The speed was increased every minute from 2 km/h (0.56 m/s) to 8 km/h (2.22 m/s) with a step of 1 km/h and after decreased every 30 seconds to 5 km/h (1.39 m/s) and 2.5 km/h (0.79 m/s). It was repeated three times, first after 6 month and second after one week.

An additional test scenario was involved for the examination of distance accuracy: Straightforward constant walking outdoor on enough long distance (~175 m) on a flat and paved ground. The distance was measured alternatively with GPS and tape line.

2.4 Cohorts

11 volunteers participating in the described treadmill scenario experiments were healthy persons between 32±13 years old, 176±12 cm height, 77±20 kg weight and a body mass index of 24±4. All of them provided informed consent.

2.5 Basic Ideas and Algorithms

The first steps in data processing – digital filtering and estimation of the orientation matrix – are executed on-board on the sensor (Roetenberg, Luinge and Slycke, 2009). Using the delivered quaternion the vectors of acquired data are converted into the inertial coordinate system CS_0 where the z-axis is vertical and the x-axis is directed to the magnetic North. The gravitation force is eliminated from acceleration and its integration can be separated between the vertical and plane motion. CS_0 is rotated so that the x-axis coincides with the estimated direction of motion. Analysing the gait pattern of the foot, i.e. acceleration, angular velocity and foot angle to vertical, gait events are identified which allow to detect precisely all gait cycles. While Perry (Perry, 2010) defines the beginning of a gait cycle at the initial floor contact we place it with respect to the needs of integration at mid stance. At this moment the foot is not moving, it stands on the floor. The initial conditions of the velocities and the distances, necessary for integration, are predetermined. More details are explained in (Loose and Orlowski, 2014 and 2015). The detection of gait cycles is executed for both feet.

2.6 Evaluation Software

We developed, implemented and tested all algorithms in Matlab®, V.: 2014b (www.mathworks.com). Figures are mainly produced in Matlab®, while tables were mostly processed in Microsoft Excel®, V.: 2010 (www.microsoft.com).

An editable MATLAB® script is available to process experimental data automatically step by step. After each step the intermediate results are saved. Figures can be created and written to hard disc.

The following steps are included:

- **Preprocessing**: reading and reorganizing sensor by sensor the acquired data, given in the sensor related coordinate system, transformation of sensor data into world coordinate system, elimination of gravity, calculation of orientation relative to the initial one, calculation of angles between z-axes of a sensor and the vertical or the horizontal plane, calculation of joint angles.
- **Processing**: estimation of direction of motion, calculation of candidates for gait events, plausibility check, determination of gait cycles, transformation of data into motion coordinate system, integration of acceleration, calculation of velocity and position data stride by stride.
- **Postprocessing**: calculation of physical and statistical characteristics for each stride and the whole walking distance, determination of average motion.
- **Evaluation**: building figures, extracting and processing tables.

The developed algorithm is described in more detail in (Loose and Orlowski, 2015).

3 DISCUSSION AND RESULTS

In this section results from all scenarios and for all sensors are presented. First evaluation results of the basic algorithm for both foot sensors in the test scenario, followed by the results of standard scenarios are listed.

3.1 Test Scenario

A quick test scenario was implemented to examine the accuracy of the determined distance. On the campus a path was identified where the subject walked two times a relative long distance straightforward on a flat and paved ground. The distance was measured with GPS (171-181 m) and a classical tape line (174.7 m) what can here used as the “gold standard”. The measured distance for the right foot is 179,6 m and the left foot 179.4 m, i.e. the absolute error is ≈ 5m and relative error < 3 %. The subject made 108 strides. The average stride duration is 1.03 s, the length 1.66 m, the height 0.12 m, the width 0.04 m and the speed 1.60 m/s. All values are plausible. The result is excellent, but not validated yet.

3.2 Walking on Treadmill

Eleven subjects participated in the walking on treadmill scenario with a speed profile from 2 km/h (scuffle) to 8 km/h (rush, jog) stepping 1 km/h. A small number of subjects switched from walking to jogging when the speed became uncomfortable (> 7 km/h). This scenario was done by 11 subjects. Seven of them executed it once in April and twice in October 2015. 46 of 68 data sets acquired from foot sensors were analyzed. 12 data sets were corrupted (interruption of the data transfer via Bluetooth).

Sabatini (Sabatini et al., 2005) used a similar scenario to assess the determination of walking features using inertial foot sensors.

3.2.1 Evaluation of the Method

A distance of 643 m was monitored by treadmill; a distance of 680 m was determined by a camera based control measurement. From all data sets an average distance of 682 m was calculated in a range from 656 to 702 m. The mean stride speed is 1.52 ± 0.05 m/s. The number of strides varies between 401 and 471 and a mean of 441. The variance of the walking distance of about ±4% results from

- a small variation of the walking time and the treadmill speed, what was not determined,
- the intra-subject variance of walking and
- a systematic error (no filtering of the impact of the heel strike) and the variance of the

calculation method (limited precision of the stride detection of ±16 ms).

Table 1 and 2 summarize averaged characteristics of the gait what were first determined for each stride, then averaged over all strides of each data set and finally statistically evaluated over all data sets.

Table 1: Averaged over all foot sensor data sets stride characteristics (min – minimum, max – maximum, mean – mean value, std – standard deviation).

	averaged stride characteristics						
	duration [s]	length [m]	height [m]	width [m]	speed [m/s]	strike angle [°]	lift angle [°]
min	1,03	1,43	0,08	0,02	1,46	17,97	58,87
max	1,21	1,73	0,17	0,06	1,59	36,32	78,80
mean	1,10	1,55	0,12	0,04	1,52	26,20	71,25
std	0,06	0,08	0,03	0,01	0,04	4,59	4,35

Table 1 shows the duration, length, height, width and the velocity of an averaged stride as well as the strike and the lift angle of the foot. The variance of the stride characteristics over all data sets can be explained by different physical properties of involved subjects, e.g. their height, leg length and level of fitness.

Table 2: Correlation coefficients of by the stride duration normalized measured and average strides. The relevant components in the sagittal plane are averaged over all data sets (min – minimum, max – maximum, mean – mean value, std – standard deviation).

	correlation coefficient				
	forward		sideward	vertical	
	acc	vel	ang. vel.	acc	vel
min	0,86	0,94	0,91	0,76	0,88
max	0,93	0,99	0,97	0,87	0,95
mean	0,90	0,98	0,94	0,81	0,92
std	0,01	0,01	0,01	0,03	0,02

Data summarize in table 2 correlation coefficients between each stride execution (normalized by the stride duration) and the average stride (determined for the data set) and their statistically evaluation over all subjects. They reflect the small variance of the stride execution in the sagittal plane, while the variance in the other direction is significant (not shown in the table). By the way these results show the excellence of stride detection. The best correlation is observed for the angular velocity and linear velocities calculated by integration of the acceleration, smoothing disturbances of the acceleration. The highest variance is seen in the vertical component of acceleration, what can be explained by the natural variance of the vertical movement of the foot and the influence of the heel strike which causes an additional pulse on the acceleration.

3.2.2 Evaluation of Stride Velocity

Every measurement of the treadmill speed can be evaluated against the adjusted treadmill speed profile. When a subject walks on the treadmill it has to adapt its walking to the speed of the treadmill in a natural way, i.e. increasing stride length and decreasing stride duration at the same time. Following the calculated stride velocity for each speed level can be interpreted as a measure of the treadmill speed.

All measurements are considered against the adjusted speed profile. The results are presented in figure 2. The plot shows that there is a very good coincidence between the mean stride length and the adjusted treadmill speed during stepping-up speed (small overestimating) and an underestimation during stepping-down speed. In the given speed range from 0.5 m/s to 2.3 m/s the differences are less than 0.1 m/s during stepping-up speed and twice of them during stepping-down speed.

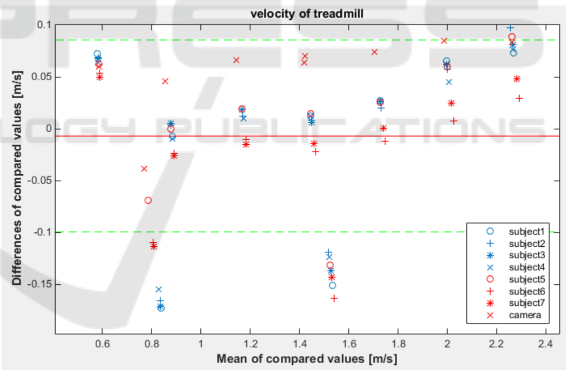

Figure 2: Differences between measured and adjusted treadmill speed against their mean. Data of seven subjects and the optical system are included. The mean of differences is shown as red line, the 1σ-environment as a green.

The beginning of a new speed level was automatically detected observing the changes of the stride velocity. If the change from one stride to the next stride (or the average of a number of strides) is higher than a given threshold the beginning of a transition phase was registered. The transition phase between two levels, where the treadmill speed rises up or slows down and the subject tries to adapt to changing the treadmill speed, is still added to the following level. From this consideration the different effects during stepping up and down speed can be explained.

3.2.3 Influence of the Walking Speed

In figure 3 the dependency of essential stride characteristics like stride length, height, width and velocity, strike and lift angle, duration of stride, stance and swing on the numbers of steps is presented. The number of executed strides corresponds to the treadmill speed which was changed every 60, later every 30 seconds. It increases together with treadmill speed (see subplot "stride velocity"). Obviously stride length, height, width, strike and lift angle rise with increasing speed, while stride, stance and swing duration descend. Rising stride velocity is achieved by ascending stride length and descending stride duration. The relationship between the stance and swing phases is changing. The stance phase becomes shorter relatively to the swing phase.

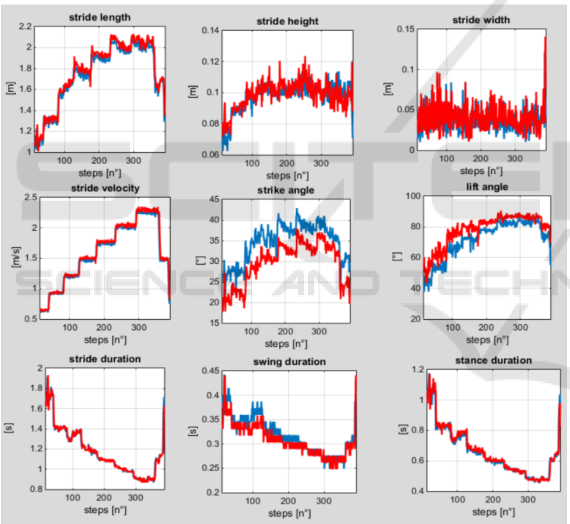

Figure 3: Influence of the treadmill speed on stride characteristics: length, height, width, velocity, strike and lift angle, duration of stride, stance and swing (red – left, blue – right leg).

After any proper stride detection statistical characteristics of all available signals can be calculated. The determination can be executed for each component or any signal vector. For any stride the mean, minimum, maximum, median and root mean square (one-stride-rms) values as well as the standard deviation of all stride characteristics were calculated. In figure 4 the rms of the components of angular velocity, acceleration and velocity in dependence on the number of steps respectively the stride velocity is presented.

Comparing the "stride velocity" (see figure 3) with the curves in figure 4 the similarity is obviously what was expected for the rms of the stride velocity. It can be suggested that there is a relationship between the one-stride-rms of the magnitude of the acquired linear acceleration/angular velocity vector and the forward stride velocity.

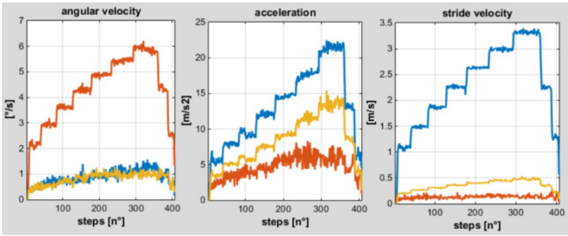

Figure 4: Influence of the treadmill speed on the stride by stride calculated root mean squares of angular velocity, acceleration and linear velocity (brown – sideward, blue – forward, ocher - vertical).

3.2.4 Estimation of Walking Speed

The relationship between walking speed and RMS of the magnitude of the angular velocity vector calculated for any whole stride is investigated on the case of seven data sets of subjects. In figure 5 the calculated for each speed level averaged RMS of magnitude of the angular velocity vector against the stride velocity is presented. The equation of the quadratic fitting curve for the mean line was determined:

$$rms = -0.36v^2 + 3.3v + 0.27 \qquad (1)$$

Obviously the quadratic curve fits the mean excellent and the seven other curves are very close to them. Equation (1) models the relationship between the walking speed, which is equivalent to the mean stride velocity, and the one-stride-rms of angular velocity vectors magnitude. To model the relationship between both values by a quadratic function seems to be satisfying, but the coefficients must be validated including more experimental data.

The Bland-Altman-Plot (Bland, Altman, 1986), shown in figure 6, points the quality of the approximation model (1). The "measured", i.e. calculated by the method described ahead, and the estimated using equation (1) one-stride-rms of the magnitude of the angular velocity vector are compared. The 1σ-environment of the differences between the values is given with ±0.12 rad/s. It seems to be that the error of the model rises with the value of the rms. The relative error is less than ±5% (worst case).

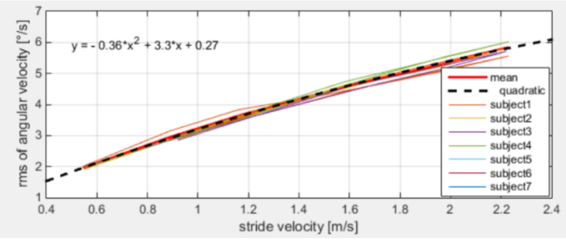

Figure 5: One-stride-rms of angular velocity over stride velocity for seven subjects. The mean is shown bold red, the quadratic fitting curve dashed black. Additional, the equation of the fitting curve is given.

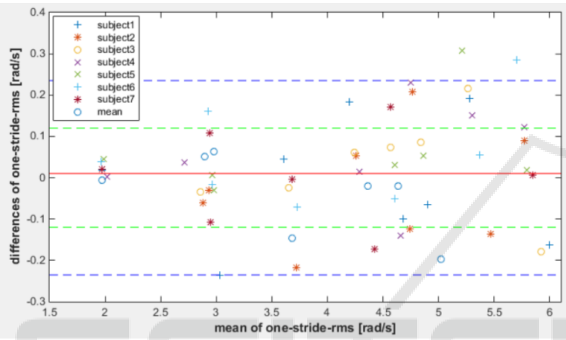

Figure 6: Differences between "measured" and estimated RMS of angular velocity magnitude over their mean. The mean of differences is shown as red line, the 1σ-environment as a green and the level of agreement as a blue line.

To determine the walking speed from the calculated one-stride-rms of the magnitude of the angular velocity vector – an inverse model is used:

$$v = 0.03rms^2 + 0.2rms + 0.049 \qquad (2)$$

On the base on the model (2) an efficient algorithm to determine gait characteristics from IMU data (angular velocity) applied to the metatarsus can be developed. After an online stride detection, i.e. the phase between two successive gait events (see e.g. Orlowski, Loose, 2014) the one-stride-rms of the magnitude of the angular velocity vector is calculated. Finally the walking speed is estimated. The walked distance can be determined. If more strides are included the results should improve.

4 CONCLUSIONS

The paper dealt with the estimation of gait parameters based on data acquired by inertial measurement units (IMU) placed at the middle foot (metatarsus). The developed method described in (Loose and Orlowski, 2015) is robust against a wide spectrum of the gait speed. The gait parameters (stride duration, length, velocity, distance) are calculated stride by stride with excellent quality. The numerical results are comparable with those of (Sabatini et al., 2005), are extended to the movement out of the saggital plane and are assessed for the full range of walking speed (2-8 km/h). This paper is focused on experimental data acquired by foot sensors during walking on the treadmill with a typical speed profile. The experimental setup, the scenario as well as the cohort were described. The accurateness and robustness of the method is shown on a test scenario, where the relative error of the determined walking distance was < 3%. Then 46 data sets of the treadmill scenario were analyzed. Statistical evaluation over the whole walking distance and over all data sets shows excellent results for essential stride parameters like duration, length, speed and foot angles as well as good results for height and width having more natural intra- and inter-subject variance. The automatically determined speed levels are evaluated against the adjusted speeds showing satisfying agreement. The results are illustrated in Bland-Altman-Plots. The influence of the walking speed on various physical and statistical stride parameters is discussed. Based on this investigation a model to estimate the walking velocity from measured one-stride-rms of the magnitude of the angular velocity vector is proposed. A further evaluation of model and its parameter using all available data sets it will be implemented for any IMU attached to the metatarsus. It is expected that the method can be applied to sensors placed above the ankle or at the trunk as well as it can be implemented on smart phones.

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