Simple Algorithms for the Determination of the Walking Distance based on the Acceleration Sensor

Katja Orlowski and Harald Loose
Brandenburg Universtiy of Applied Sciences, Department of Computer Science and Media, Brandenburg an der Havel, Germany

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Abstract: The paper presents simple algorithms for the estimation of displacement based on inertial sensors and integration of the horizontal acceleration. Experiments were conducted including nine healthy subjects. They were asked to walk three distances (20, 40 and 60m) at different speeds (normal, slow and fast). The acceleration and the angular velocity vectors ere captured by inertial sensors from SHIMMER research and Xsens technology fixed to the lower shank. Two algorithms - whole signal integration and stepwise integration - were compared with regard to their accuracy. A priori knowledge about the motion was included in the calculation. Statistically all methods work well (mean of the relative distance is 0.97 while the variance is not negligible ($\sigma = 9\%$). The quality of the results depends especially on the tempo of motion.

1 INTRODUCTION

"Personal navigation" has been a discussed topic in the last few years. Inertial and ground reaction sensors are used in personal navigation system (PNS). Sensor based PNS are conceivable as a component of ambient assisted living (AAL) systems, in healthcare or in tele-medicine. They can be used for monitoring the activity of elderly people, e.g. to monitor the daily covered distance or to get an overview about burnt calories.

PNS based on inertial sensors are called inertial navigation system (INS). Suh and Park (Suh and Park, 2009) describe them as assisting for firefighters or security personnel. Bird and Arden (Bird and Arden, 2011) report that in the military environment accurate navigation information is of importance.

Pedometers, as an other PNS, count the number of steps (strides). Based on the known mean length of a stride, entered during the personalizing of the pedometer, the covered distance is determined. The problem consists in the variation of the step length due to the walking velocity and the form of the day (Cavallo et al., 2005) and section "Results" below). If a person walks slower the step length is shorter, while at fast walking the step becomes longer. It is debatable whether the various lengths of steps in the course of a day compensate each other. Furthermore, the accuracy of the pedometer depends on the quality of the step counter[1]. It is assumed that personal navigation system based on inertial sensors work better in measuring covered distances and consumed calories than pedometers.

Global positioning system (GPS) can be used alternatively in personal navigation systems. GPS is receivable only outdoors, so they cannot be applied inside buildings (Bebek et al., 2010; Suh and Park, 2009; Pratama et al., 2012; Bird and Arden, 2011). Assisted GPS (aGPS) overcomes the weakness of GPS inside of buildings. AGPS includes information provided by other sources (Wi-Fi, mobile networking) in order to improve the navigation in signal-poor environments. Feng and Law (Feng and Law, 2002) presents the impact of aGPS on navigation.

The estimation of covered distances based on inertial sensors is a big challenge. Sophisticated methods using the accelerometers, gyroscopes and magnetic compass in combination with Kalman filter techniques were proposed and implemented, amongst others, by Welsh (Welsh, 1996) and Xsens (Xsens Technologies B.V., 2012). The 3D motion of the sensors fixed to the person's body and the sensor drift and noise cause serious problems. In addition, the process of double integration to get the displacement from acceleration leads to an accumulation of errors and

[1]Comparison of step counters http://igrowdigital.com/-de/2013/03/praxistest-wie-genau-messen-schrittzahler/

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implicates the necessity to find the free parameters - the initial velocity v_0 and v_{min} and displacement s_0. Non-zero-updating and correction methods based on a priori knowledge about the motion were introduced by different authors (Roetenberg et al., 2009; Welsh, 1996).

The purpose of this investigation is to develop a simple algorithm for the calculation of distances covered while walking when sensors measure acceleration and angular velocity. Simplicity of the algorithm means that there is no information about the orientation of the sensor. The algorithm is implementable on mobile devices like mobile phones. This paper presents two simple approaches based only on one component of the acceleration and angular velocity. The algorithms are compared using datasets collected in walking experiments with different distances and speeds. Furthermore, the influence of variations of filter parameters and stride determination is investigated.

2 SYSTEMS AND EXPERIMENTS

2.1 Systems

Mobile inertial sensors developed by Shimmer Research (Shimmer Research, 2011) and Xsens Motion Technology B.V. (Xsens Technologies B.V., 2012) are used to measure acceleration a and angular velocity ω during the gait of healthy subjects. The measured data is transferred wireless via bluetooth to the supervising PC (laptop). Important parameters are presented in table 1. Before starting measurement, inertial sensors need to be calibrated on the gravity acceleration. For Shimmer sensors the 9-DoF-Calibration software is used to calculate the offset and the scaling factors.

Table 1: Technical data of Shimmer and Xsens (accelerometer and gyroscope).

	Sampl. Freq.	Range	Res.
Acc_S	51.2 to 1024 Hz	1.5 g, 6 g	12 bit
$Gyro_S$	51.2 to 1024 Hz	500 deg $/s$	12 bit
Acc_X	20 to 150 Hz	16 g	12 bit
$Gyro_X$	20 to 150 Hz	1200 deg $/s$	12 bit

The calibration procedure of Xsens software is an one minute phase to determine the initial orientation of the sensor. The internal acquisition of data is processed with a frame rate of 1800 Hz, strapped down by integration (SDI) to the automatically chosen transfer rate dependent on the number of sensors connected to the radio station (Xsens Technologies B.V., 2012). In the case of two connected sensors the frame rate is set to 100 Hz. The preprocessing on the sensor includes the estimation of the mean values of acceleration, angular velocity and orientation (e.g. rotation matrices, Euler angles or quaternions). Xsens provides very accurate synchronization of integrated sensor components. Xsens motion tracking sensors (MTw) are applied not only in motion analysis, but in motion capture using 17 inertial sensor to determine the 3D position of human joints (Xsens Technologies B.V., 2012; Bai et al., 2012; Liu et al., 2012).

2.2 Setup

Two Shimmer and two Xsens sensors are attached laterally above each ankle, as shown in figure 1. The main plane of the sensors was aligned visually in the sagittal plane of the subject, so that the sensor fixed x- and y-axes are placed in the x-y-plane of the inertial coordinate system. There are differences between both sensor types and the left and right side of the body (see figure 1). The software Multi-Shimmer Sync and Xsens MT Manager were used to process, to transfer and to store captured data. The calibration of all sensors was executed once before starting the experiments. The range of the Shimmer acceleration sensor was set to $\pm 1.5g$. No synchronization was achieved between both systems.

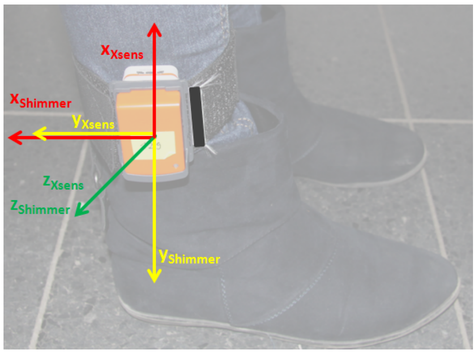

Figure 1: Alignment of the sensors lateral above both ankles in the sagittal plane of the subject. Additionally the differences between the coordinate systems of Shimmer and Xsens are highlighted.

2.3 Experiments

During the experiment the acceleration and the angular velocity are stored and simultaneously captured with Shimmer-6-DoF- and Xsens MTw sensors. The gait of eight healthy subjects (mean height (std): $170.8cm$ ($\pm 7.84cm$)) was observed. All distances (20, 40 and 60 m) were covered twice at slow, normal and fast pace. Each subject chose the speed for normal, slow and fast walking itself. The distances were measured with a conventional measuring tape (accuracy of 1 mm) and marked by the investigators. The frame rate of the Shimmer sensors was 102.4 Hz with the exception of two complete datasets (51.2 Hz).

The experiment took place outdoors on a sunny summer day, with no appreciable wind speed. Influences caused by the weather can be neglected.

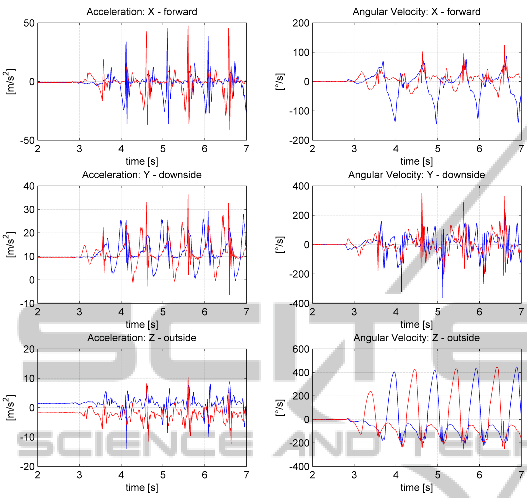

Figure 2: Raw data of Xsens sensors (left - blue, right - red).

2.4 Preprocessing

The preprocessing includes four steps:

1. Reading, reorganizing and renaming the experimental raw data of both systems: As a result of that step, acceleration and angular velocity of every passage are collected in one dataset. The three components (x,y,z) of them are oriented along the correspondent axes of the inertial coordinate system (compare figures 1 and 2).
2. Attuning the signals of both sensor types to common sampling intervals given by the lower sampling rate (mostly 100 Hz): The smaller dataset is interpolated to reach the same length and time resolution of the larger dataset.
3. Synchronizing the signals of both sensor types using correlation between the angular velocities ω_z: The distance between the cross correlation of the signals of both systems and the auto correlation of Shimmer signals is calculated and applied to shift the Shimmer signals.
4. Cutting the resting phase before and after the motion, so that the movement signals are integrated (forward velocity v_x is positive).

The results of preprocessing are presented in figure 3.

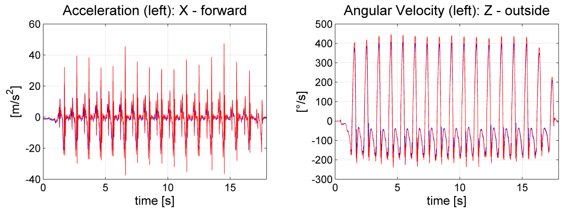

Figure 3: X-axis of acceleration and z-axis of angular velocity after preprocessing (blue Shimmer, red Xsens).

2.5 Discussion

After preprocessing 103 out of 144 datasets were extracted for further investigation. 41 datasets were rejected because of the missing or erroneous data. Xsens data mark incorrect values with "NaN", which were removed manually before preprocessing.

There is no substantial difference between the measurements of acceleration and angular velocity of Shimmer and Xsens sensors. Caused by the chosen sensitivity of $\pm 1.5g$ the Shimmer acceleration signals are limited at $\pm 20m/s^2$. Higher peaks are cut.

Table 2 summarizes the dependencies between the walking velocity, the covered distance and the chosen speed. Analogue to that the number of strides are shown. The dependencies coincide with our expectation. The stride number is greater, the higher the pace and the longer the distance, but it rises underproportionally with the distance. Ergo, the stride length is larger and the mean velocity higher, the longer the distance. The measured velocity corresponds to the chosen speed. These facts have been evidenced by the measured gait sequences.

Table 2: Mean velocity in m/s (std) and mean number of strides (std).

	slow	**normal**	**fast**
20 m	1.05 (0.1)	1.25 (0.08)	1.5 (0.12)
40 m	1.17 (0.08)	1.36 (0.13)	1.53 (0.1)
60 m	1.21 (0.09)	1.4 (0.08)	1.71 (0.13)
20 m	16.2 (4.6)	14.2 (3.8)	13.2 (3.4)
40 m	25.7 (8.5)	26.6 (8.3)	22.5 (5.7)
60 m	40.8 (13.0)	37.7 (10.9)	33.4 (8.3)

While the standing before and after the acceleration sensors measure only the gravity acceleration $g = -9.81m/s$. If the alignment of the sensors in the sagittal plane is ideal, a_x and a_z are zero while a_y is equal to g. Two mentionable types of errors are:

- The norm of the acceleration vector differs from g (see figure 4). It was calculated and averaged in an interval of 1 s before motion.

- The observed a_x and a_z differs from zero, i.e., the gravity vector participates to these components.

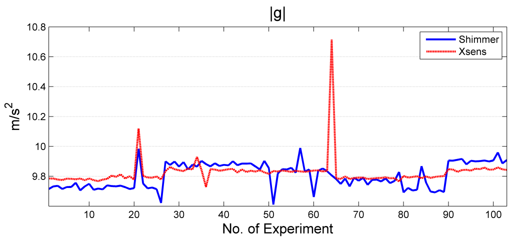

Figure 4: Measured vector of gravitation before motion representing the problem of calibration and sensor drift.

3 METHODS

The sensors are fixed to the lower shank above the ankle and move all the time with the shanks changing their orientation. To calculate the covered distance only the component in the direction of motion is of interest. Following the vector of acceleration has to be projected to the horizontal component $a0_x$ in the sagittal plane (of inertial coordinate system). In principle, different approaches are possible:

- To calculate all kinematic features including the forward motion from the sampled data. The mathematical background is given in (Loose and Orlowski, 2012), but the accumulated error is growing with the duration of motion.
- To estimate the orientation of the sensor coordinate system (Xsens), to project the acceleration on the x-axis of the inertial coordinate system and to integrate it twice to get the covered distance s.
- To estimate the vector of acceleration $a0$, of velocity $v0$ and of distance $s0$ as well as the angular velocity ω and the orientation matrix R using the Kalman filter technique (Welsh, 1996)
- To approximate the needed component $a0_x$ using one or two components of the acceleration.

All approaches need additional and/or apriori knowledge about the motion, e.g. initial and intermediate state information or integral properties of the process:

- There is no motion before and after measurement, i.e. initial and final velocity is equal to zero. The integral of acceleration over the whole time is equal to zero, too.
- The motion is straight forward, i.e. the forward velocity is always greater than zero ($v >= 0$) and, following, the velocity of the ankle is $v > v_{min} > 0$ during motion.
- The vertical motion of the ankle and the declination of the shank from the vertical are relatively small (with regard to the horizontal motion).
- The motion is nearly periodic and stride-based.
- The horizontal component of the ankle is $v_x >= 0$, $y = y_{min}$ before and after stride for each leg.

In this paper only the measured components a_x and ω_z are used to calculate the covered distance. The simplification is based on the assumption that the declination of the shank from the vertical is small. In that case the gravity can be eliminated and the vertical acceleration neglected. The DC part of $a0$ and ω is eliminated by high pass and the noise by low pass filtering. The integral of the AC part over the whole motion (each stride) must be zero because of the periodicity of motion (stance phase of each leg).

Two different methods are investigated: whole signal and stepwise integration (stride).

Both approaches start with band pass filtering of the acceleration a_x and angular velocity ω_z. The stop and pass frequencies of the low pass were set to 20 and 10 Hz. The influence of the filter parameters, especially the pass and stop band of the high pass, were investigated. The high pass is used to eliminate systematic offset of measurement and the gravity. The pass frequency must be less than minimum stride frequency ($\sim 0.7Hz$). The following pairs of stop and pass frequencies (in Hz) were tested: $[0.25, 0.6], [0.2, 0.5], [0.15, 0.3], [0.1, 0.2], [0.05, 1]$.

The best results were achieved using the second pair. The results of optimal filtering are shown in figure 5.

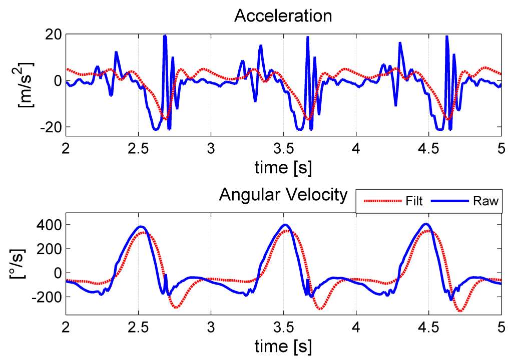

Figure 5: Raw and filtered signal of a_x and ω_z.

Whole Signal Integration (WSI)

- Integrating a_x using an IIR-filter with the kernel [0.5 0.5]/[1 -1] (trapezoid rule).
- Adding an offset $min(v_x)$ to v_x, so that $v_x \geq 0$.
- Calculating s_x from v_x using the same filter.

Stepwise Integration (SWI)

- Detecting the feature points representing the begin and the end of a stride, for left and right leg, respectively.

- Calculating the covered distance s_x for any stride by integrating a_x, adding an offset to v_x, so that $v_x > v_{min} > 0$; where $v_{min} = 0.15 * mean(v_x)$, calculating s_x integrating v_x.
- Accumulating all single distances to the covered distance s.

Three variants for the detection of strides were investigated (see figure 6):

Method S1. The maximum angular velocity ω_z is the point characterizing the start/final point of any stride. These points lie a bit after the maximum velocity v_x and before the maximum deceleration $-a_x$.

Method S2. The maximum deceleration $-a_x$ is the point characterizing the start/end point. These points lie a bit before the terminal contact (TC).

Method S3. The swing phase of a stride is defined by TC to the initial contact (IC) of the foot on the ground. Following, the stance phase is defined by IC and TC. Algorithms to detect these points are found in (Orlowski and Loose, 2013; Greene et al., 2010). Here any stride lasts from one TC to next one.

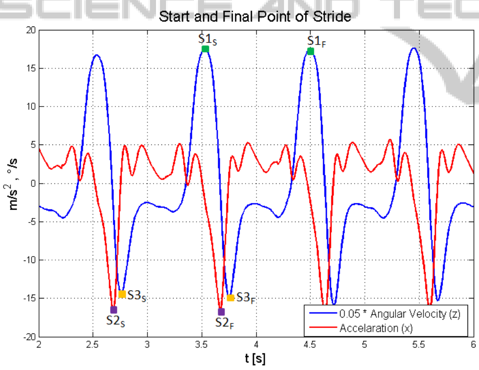

Figure 6: Start and final point of stride for methods S1-S3.

4 RESULTS

Figure 7 shows typical curves of the kinematic characteristics: linear acceleration, velocity and displacement, angular velocity and angle.

The covered distance is the most important calculated value characterizing the quality of algorithms. The "relative distance" d_{rel} is a measure of that goodness: $d_{rel} = d_{calc}/d_{abs}$.

The mean over all calculations after elimination of obvious outliers is $0.97 \pm 0.09\sigma$, the relative error is $3\% \pm 9\%$. That feature depends on the walking distance as well as on the chosen speed (see table 3).

The best result is achieved in the case of normal pace ($0.97 \pm 0.07\sigma$). For slow motion the distance is overestimated, while for the fast it is underestimated. The reason is that the algorithm was adjusted for normal speed and 20 m distance.

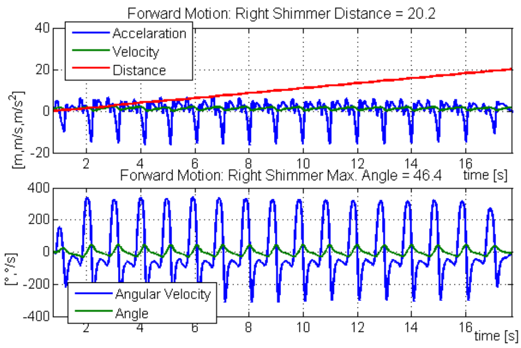

Figure 7: Kinematic characteristics for one leg of a subject.

Table 3: Relative distance - mean (std).

	slow	**normal**	**fast**
20 m	1.1 (0.1)	0.97 (0.07)	0.89 (0.1)
40 m	0.96 (0.07)	0.96 (0.1)	0.89 (0.08)
60 m	1.05 (0.08)	1 (0.07)	0.93 (0.09)

Table 4: Relative distance on method.

method	**A1**	**S1**	**S2**	**S3**
mean	1.04	0.8	0.98	0.98
std	0.1	0.09	0.1	0.1

Table 4 shows that all four algorithms work well. The algorithm A1 (WSI) overestimates the distance ($4\%(\pm 10\%)$) while the SWI algorithms (S2, S3) are comparable and underestimate the distance ($2\%(\pm 10\%)$). The underestimation can be easily compensated adjusting the parameter v_{min}.

Comparing the calculated distances based on the data captured from Shimmer and Xsens sensors, Shimmer data returns shorter distances than Xsens data (37.0 m vs. 39.6 m for left and 35.2 m vs. 37.7 m for right side). The difference between both sensor types is caused by the limitation of $\pm 1.5g$ set for Shimmer sensors. The difference between the left and the right side can be explained by the fact that the subjects start motion with a half stride of one leg and finish with a half stride of the same or the other leg.

The inter class variability has been investigated. There are some differences which are explainable by the different number and types of datasets, i.e. all distances and speeds are included into the evaluation. There are dependencies between the relative distance and the velocity as well as the number of strides and the calculated distance.

Figure 8 shows results for all datasets with respect to the covered distance. The relative distance is presented. There is a relatively high number of outliers. Strides greater than 2 m or less than 0.5 m are not existent during walking of healthy adults.

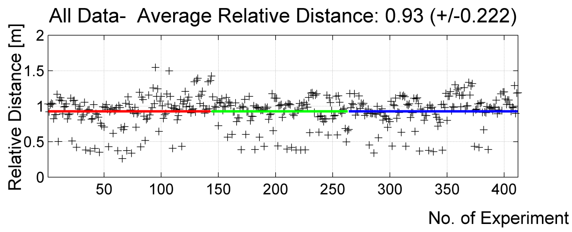

Figure 8: Average relative distance sorted by distance (20 m - red, 40 m - green, 60 m - blue).

5 DISCUSSION AND CONCLUSIONS

The purpose of this investigation was to develop a simple algorithm for the calculation of the distance covered while walking. Simplicity in that case means that there is no information about the orientation of the sensor. The algorithm is implementable on mobile devices like mobile phones. The investigated algorithms were based on the "horizontal" components a_x and ω_z. Two different approaches, were implemented and compared (WSI vs. SWI). Statistically all methods work well. The mean of the relative distance is 0.97, but the variance is not negligible $\sigma = 9\%$. The quality of the results depend on the speed of motion. A large number of outliers were determined and the reasons must be analyzed. The source of errors caused by calibration can be reduced, i.e. by recalibrating sensors any time before every subject.

The algorithms will be improved in the future including e.g. the vertical component of the acceleration, the declination of the sensor at the beginning and during the motion. A comparison with Kalman filter approaches and the determination of the orientation delivered by Xsens sensors have to be conducted.

Further experiments such as walking on a treadmill at different speeds are planned. It seems to be that simple algorithms based on acceleration and angular velocity can satisfy everyday needs.

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