Indoor Localization Using A Smart Phone

Rui Zhang, Amir Bannoura, Fabian Höflinger
Leonhard M. Reindl, *member*, *IEEE* and Christian Schindelhauer*, *member*, *IEEE*
Department of Microsystems Engineering, Department of Computer Networks and Telematics*
University of Freiburg
79110, Freiburg, Germany
Email: rui.zhang@imtek.uni-freiburg.de

***Abstract*—This paper presents a novel indoor localization solution using a smart phone. Instead of building the inertial measurement unit (IMU), the integrated calibrated sensors inside the smart phone provide all the sensor information needed. Meanwhile, we avoid the complicated calibration process, when the calibration machines or workstations are not available. Since smart phones are meant to be held in hand, algorithms and methods based on walking speed reset can not be utilized. Therefore, correct orientation and step length information are indispensable. In this study, a modified Kalman filter based sensor data fusion was used to achieve accurate orientation data by detecting and minimizing the effect of magnetic field disturbance. Three methods are presented and compared to calculate each step length based on vertical acceleration using biomechanic model or empirical relation. The experimental results show that the proposed solution is capable of tracking the person indoors and to achieve a tracking accuracy of less than 0.3m.**

***Index Terms*—smart phone, indoor localization, IMU, Kalman filter, Step length.**

I. Introduction

Although personal localization and navigation are becoming available to the general public and businesses via widespread use of Global Positioning System (GPS) receivers, GPS signal can be blocked by high buildings, canyons or forests. Thus, indoor localization can not rely on GPS. There are numerous non-GPS approaches to track and navigate personal position [1]. But most of these systems normally require external references. The pre-installation of these external references make these systems inconvenient to use.

An alternative solution is pedestrian dead reckoning. By using MEMS inertial sensors (accelerometers, gyroscopes), ones position can be calculated recursively based on acceleration and angular rate of the movement. Moreover, this system does not depend on the environment where pedestrians are located and it requires no external references.

Through our previous study on building our own inertial localization system, we found that besides the challenges in designing an algorithm, the accurate calibration of the sensors could be a significant problem if professional calibration platforms or facilities are not available [2]. The same algorithm can deliver better results using calibrated sensors compared the ones without calibration.

Thanks to the rapid development of mobile phone technology. Smart phones can be a proper potential candidate as a personal localization system due to its functionality and popularity. Besides GPS and wireless infrastructure based personal localization, new generation of smart phones are able to play a role as an inertial measurement unit (IMU), since all the sensors required are already integrated inside the phone. Furthermore, the sensors in the smart phone[1] used in this study was found already calibrated compared to Xsens' MTx IMU-module[2]. In this case, no extra hardware implementation and calibration facilities are needed. Software can be immediately tested without considering the hardware issues.

Although there are many literatures focusing on the indoor localization using smart phone, to the authors knowledge, none of them is able to give a complete description about both orientation and gait length estimations. Trehard *et al.* presents a solution by integrating an anemometer to the smart phone for speed estimation [3]. In their approach, the orientation information is obtained directly from the smart phone, which will be easily disturbed by local magnetic field and can not be relied on to achieve high positioning accuracy. Kim and Kim use geomagnetic field to obtain the position information [4]. However, the database in respect of geomagnetic field at each location has to be constructed previously. Hong *et al.* provides an orientation solution based on the work from Jiménez [5] and Foxlin [6], which uses heuristic drift elimination and turns insufficient effect to compensate drift bias [7]. Since the solution is magnetic-field-free, sometimes the obtained orientation might become unreliable. Besides, no information about step estimation is given.

In this study, an inertial sensor based personal localization using a smart phone is presented. A modified Kalman filter based sensor data fusion is used to achieve accurate orientation information, and meanwhile the vertical accelerations are used to obtain the gait length of each step. The experimental results showed that the correct trajectory could be successfully obtained.

II. Orientation Determination

Sensor data fusion using Kalman filtering is implemented to obtain the correct orientation data. The reader of this paper is referred to our previous study [8] for implementation details, nevertheless some key aspects will be highlighted here.

In our Kalman filter, we model the system state as the orientation error $\delta\Theta$ and the angular rate error $\delta\Omega$. We

[1] http://www.samsung.com/global/microsite/galaxys2/html/feature.html
[2] www.xsens.com

use the difference between the gyro-based and the magnetic field/acceleration-based orientations for measurements. Through this state and measurement representation, we avoid to model the non-linear system behavior. The structure of the system is shown in Fig. 1.

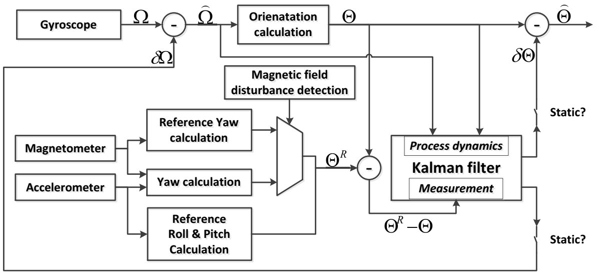

Fig. 1. Kalman filtering structure for orientation determination.

At the beginning, the angular rate data Ω of the three-axis gyroscope is corrected by subtracting the bias error $\delta\Omega$ estimated from the Kalman filter based sensor data fusion, which will be mentioned in the following. Then, the gyro-based orientation Θ is calculated from the corrected angular rate $\hat{\Omega}$ using the navigation equations and Quaternion algebra. The orientation is presented by three Euler angles: Roll, Pitch and Yaw, as shown in Fig. 2.

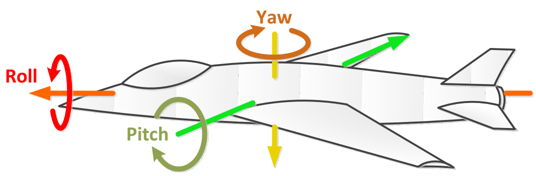

Fig. 2. Euler angles.

For the calculation of the orientation reference, we combine the three-axis magnetometer and accelerometer data to obtain another set of orientation data Θ^R using the local magnetic field and gravity information. Since the reading of accelerometer is the addition of gravity and the acceleration due to the movement, the reference orientation can only be calculated if the reading of accelerometer is static, which means that the norm of the acceleration data is close to the value of the gravity and the acceleration due to the movement is very small compared to the gravity. The difference between the gyro-based and magnetic field/acceleration-based orientations $\Theta^R - \Theta$ is utilized as filter measurement to correct the state: orientation error $\delta\Theta$ and gyro bias $\delta\Omega$.

After Kalman filtering, the corrected orientation $\hat{\Theta}$ is obtained by subtracting $\delta\Theta$ from Θ using Quaternion algebra. It can be seen that $\hat{\Theta} = \Theta$ and $\hat{\Omega} = \Omega$ if the acceleration data is not static. Therefore, the incorrect Θ^R will not affect the resulted $\hat{\Theta}$.

However, magnetometer can be easily affected by local magnetic field disturbances, incorrect Θ^R can result in incorrect $\hat{\Theta}$. In order to overcome this problem, a functionality detecting and minimizing the magnetic field disturbances is added to the filter structure. By processing the reading of magnetometers and accelerometers, the magnetic disturbances can be successfully detected. If disturbances happen, another set of magnetic field vector generated by Θ instead of the reading of magnetometers is used to calculate the Θ^R. Hence, the impact of disturbances can be minimized.

In comparison to the method implemented in literature [5], [6], [7] and [9], our method of orientation determination does not depend on step information, which means that our method can still be utilized even if there is no walking-like behaviors during the movement.

III. Position Calculation

In order to obtain accurate position information, zero velocity update method is commonly used to correct the velocity and acceleration [10]. However, it is not convenient to attach the smart phone to the foot, not only due to its comparably large size, but also because a phone is meant to be held in hand or in the pocket. Thus, the normal pedestrian dead reckoning (PDR) method has to be applied. PDR is simply the estimation of a step length (or walking speed) and the direction of walking. The position information is determined if the step length, direction and number of steps are obtained.

A. Step Detection

Based on the method from [11], each step can be detected by acceleration signals and step boundaries are defined by the positive-going zero crossings of a low-pass filtered version of vertical acceleration signal acc_Z as shown in Fig. 3. A 2^{nd} order Butterworth low-pass filter with cut-off frequency of 10 Hz is used in this study. Positive-going zero crossing means that the signal is smaller than zero at last time step and larger than zero at the following time step.

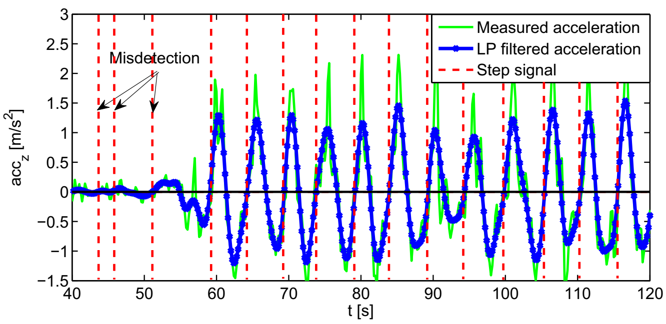

Fig. 3. Step detection using zero crossing method.

It can be seen clearly from Fig. 3 that there are misdetections existing. Even a small vibration at the beginning will cause a step signal. It will result in an incorrect start point especially when the constant step length is used. An alternative solution is to use two thresholds to detect the steps, as shown in Fig. 4. If the absolute value of acceleration signal is smaller than either one of the thresholds, no step is detected. In this way, the step detection accuracy is enhanced only if the proper threshold can be set. The fact is that it is very difficult to determine the correct threshold so that vibrations and small forced steps can be differentiated. However, since this study focus on variate step length determination, the step length of vibration is very small. Therefore, the impact of misdetection on the positioning using positive-going zero crossing method can be eliminated.

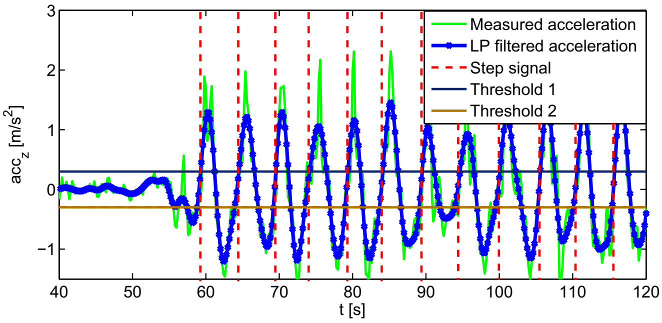

Fig. 4. Step detection using two thresholds method.

B. Step Length Determination

In the literatures, there are well described algorithms to estimate each step length using acceleration data. According to [12], [13], the step length estimator is based on the biomechanic model of a kneeless biped. The acceleration is measured at the center of the mass, which is defined as a point at the back of the subject at the level of the fourth lumbar vertebra. The vertical displacement of the mass center during one step is calculated by

$$h_k = \int \int_{t_k}^{t_k+\Delta T_{a,k}} a_v dtdt, \tag{1}$$

where t_k is detected time stamp of k^{th} step, a_v is the vertical acceleration, and $\Delta T_{a,k}$ is the time duration when $a_v \geq 0$ within k^{th} step. The kneeless biped is modeled as an inverted pendulum. With known leg length l, the step length of k^{th} step is obtained by

$$SL_{k,1} = C_1 \sqrt{2lh_k - h_k^2}, \tag{2}$$

where C_1 is a constant parameter for tunning the result.

The second method introduced in [14] uses an empirical relation of the vertical acceleration and the step length.

$$SL_{k,2} = C_2 \sqrt[N_2]{a_{v,k}^{max} - a_{v,k}^{min}}, \tag{3}$$

where $a_{v,k}^{max}$ and $a_{v,k}^{min}$ are the maximum and minimum value of the a_v within step k. C_2 and N_2 are constant parameters for tunning the result.

The third empirical method based on [15] using mobile devices is given by

$$SL_{k,3} = C_3 \sqrt[N_3]{\overline{|a_v|}_k \cdot \sqrt{\frac{M_3}{\Delta T_k \cdot (a_{v,k}^{max} - a_{v,k}^{min})}}}, \tag{4}$$

where $\overline{|a_v|}_k$ is the average of the absolute vertical acceleration values within step k, ΔT_k is the time duration of step k, C_3, N_3 and M_3 are constant parameters for tunning the result.

Since in this study the measured acceleration comes from a hand-held smart phone other than in-pocket or waist/back attached devices, some tuning constants might need adjustment. More detail discussion and comparison of these three step length estimators can be found in [16].

With the time stamp of k^{th} step signal t_k and its corresponding Yaw angle $\psi(t_k)$, the 2D position $P_k = [p_{x,k}, p_{y,k}]$ after k steps can be recursively calculated by

$$p_{x,k} = p_{x,k-1} + SL_k \cdot \cos(\psi(t_k)), \tag{5}$$

$$p_{y,k} = p_{y,k-1} + SL_k \cdot \sin(\psi(t_k)), \tag{6}$$

where SL_k is the determined step length of k^{th} step based on the methods mentioned above.

IV. Experimental Result

Experiments took place inside our lecture halls building. During the experiments, a smart phone with an MTx IMU-module (Xsens Technology) attached to the phone was held by a person, who walked inside the building, as shown in Fig. 5. The plain map of the floor for experiment together with a walking trajectory consisting of 54 fixed-length steps are given in Fig. 6. During the experiment, each step has to start from the mark on the ground to control each step length, thus the accuracy of the estimated step lengths can be evaluated. The orientation accuracy was evaluated using the orientation outputs from MTx as a reference.

Fig. 5. Experimental setup.

A. Orientation Comparison

It can be seen from Fig. 7 that the Yaw angles obtained using Kalman filtering based data fusion are very close to the ones from the MTx IMU-module. The angle difference between start and end point is less than 0.5°. On the contrary, the Yaw angle reading from the smart phone shows some disturbances between 24 s-35 s, which might be caused by the stairs handle

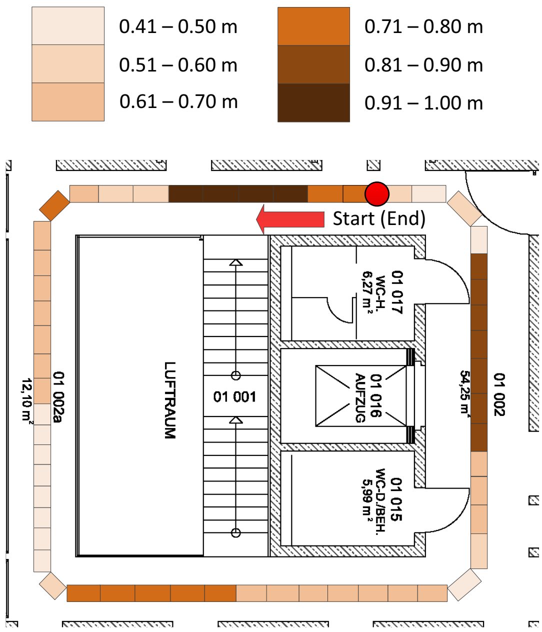

Fig. 6. Building plain map and walking trajectory.

made of ferromagnetic material. Therefore, there is a high probability that the orientation provided by smart phone itself is actually magnetic field/acceleration-based orientation Θ^R and no magnetic field disturbance minimization or sensor data fusion was implemented.

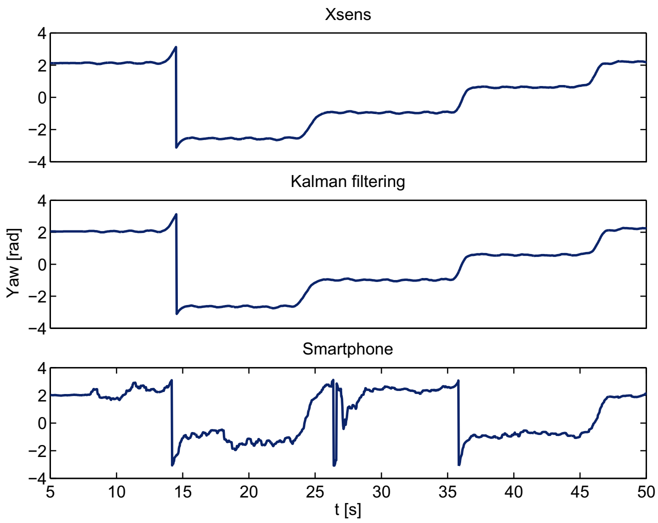

Fig. 7. Comparison of different Yaw angles.

B. Step Length Comparison

The results of step length estimation using the three introduced methods are shown in Fig. 8, where SL_n refers to step length estimated using method n. The tuning constant C_1 of the first method is chosen as 6.3. The tuning constants C_2 and N_2 of the second method are chosen as 0.4 and 2. The tuning constants C_3, N_3 and M_3 of the third method are chosen as 0.1, 1.3 and 200.

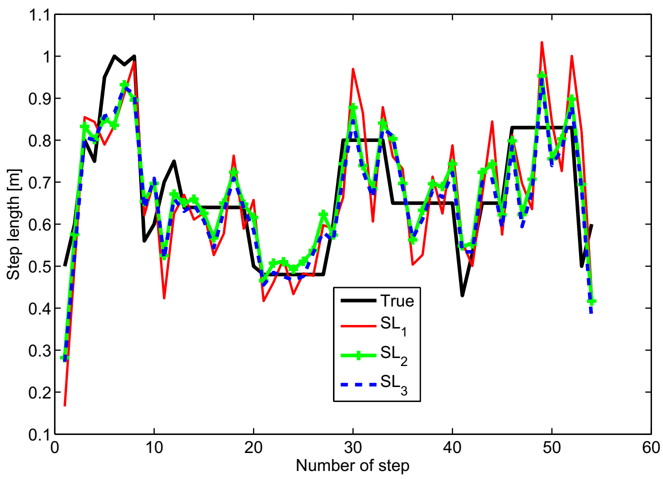

Fig. 8. Comparison of step lengths using different methods.

TABLE I
MEAN OVER TIME OF ABSOLUTE POSITION & STEP LENGTH ERROR

[m]	X-Position	Y-Position	Step Length
SL_1	0.1581	0.2626	0.1024
SL_2	0.2351	0.2405	0.0753
SL_3	0.2264	0.1509	0.0736

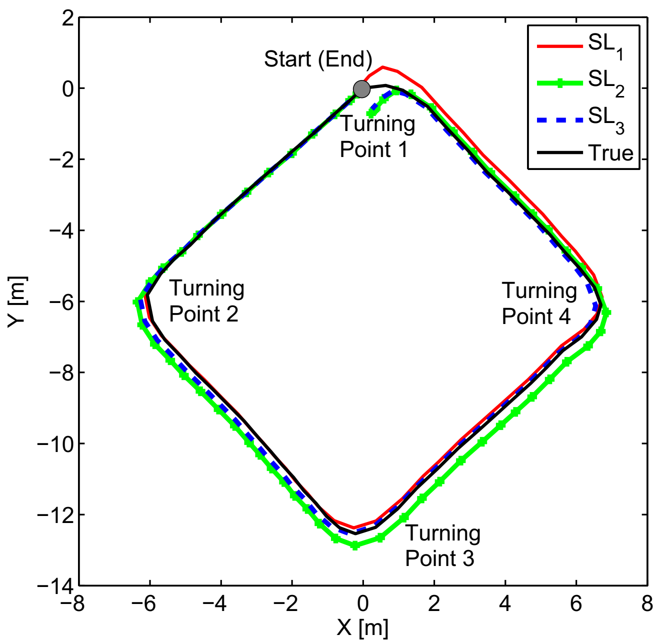

Fig. 9. Comparison of trajectories using different methods.

It can be seen that the tendency of the estimated step lengths follows the tendency of the true step length values. However, the obtained step length does not meet the true value but changes along the true value due to the manual control of the experiment, since each step length will not fit the exact length between the markers during walking. Moreover, the cut-off frequency choice of low pass filter also produces impact on the variation. The changing variance of method 1 is the largest among all the methods. The maximum value is about 0.2 m. Methods 2 and 3 perform similarly with smaller changing variance. The mean over time of absolute step length errors of three methods are shown in Table I.

The tracking trajectories using three methods are shown in Fig. 9. The tracking trajectory of method 1 has large positive position errors in X and Y directions between the fourth turning point and the end point. The tracking trajectory of method 2 has large negative position error in Y direction between the second and fourth turning points. The tracking trajectory of methods 3 has smaller negative position errors in X and Y directions between the second and third turning points. The mean over time of absolute position error in two directions is shown in Table I, which shows that method 3 performs better than the other two methods.

V. Conclusion

This paper presented an indoor localization solution using a smart phone. Correct direction information was achieved by Kalman filter based sensor data fusion using the integrated sensors inside the phone. Three methods were introduced to provide an adaptive step lengths by analyzing vertical acceleration data. The experimental result showed that the obtained trajectory was able to follow the true trajectory.

The next step is to use a motion capture system to enhance the accuracy of the true step lengths, and to further study the performance of each method. Besides, the application installed on the smart phone needs to be programmed to perform the localization in real-time and to show the trajectory result on the screen of the phone. Furthermore, a study to obtain the correct yaw angle information while the smart phone inside the pocket needs to be conducted.

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