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Pedestrian Dead Reckoning with Particle Filter for Handheld Smartphone

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Abstract— **Commonly used Global Navigation Satellite Systems (GNSS) are inappropriate as Location Based Services (LBS) in indoor environment. Therefore research teams are developing different systems, which can be used as a suitable alternative. One of options is to use Inertial Navigation System (INS) which consists of inertial sensors and mathematic procedures. This concept has been known for a long time, but with arrival of Microelectro Mechanical System (MEMS) INS found wide use. Smartphones with inertial sensors, such as accelerometers and gyroscopes, allow us to use them as input devices for Pedestrian Dead Reckoning (PDR). In this paper we present PDR by using smartphone sensors. They can be classified as low-cost Inertial Measurement Unit (IMU), and have been compared with more precise and expensive Xsens IMU. Accuracy of inertial sensors has increased in the past few years, but they still cannot alone provide proper accuracy because of many negative effects, such as heading drift due to gyroscope bias. Particle Filter (PF) has been successfully used with map constraints to increase the accuracy of proposed location system. Presented results show that low-cost smartphone IMU combined with PF can be applicable as proper navigation system.**

Keywords—Pedestrian Dead Reckoning; Particle Filter; Inertial Measurement Unit; Gyroscope; Accelerometer

I. INTRODUCTION

Navigating via Global Navigation Satellite System (GNSS) has become an important part in smartphone´s daily use. Even though GNSS provides fairly good location information in open-space, there are still areas, e.g., urban canyons, valleys and indoor environment, where localization is restrained. In order to carry out the positioning also in restrained areas with pedestrians, one possible solution is to use Pedestrian Dead Reckoning (PDR). PDR is a sequential navigation technique where the actual position is estimated from previous position whenever a step is detected. A basic concept of PDR is presented, e.g., in [1]. Conventionally, accelerometer data is used for step detection. Multiple detection methods have been developed, e.g., peak and zero crossing detection [2]. To obtain position update, step length and heading information are also needed. Step length is influenced by many factors such as age or gender and thus it is one of the challenges in PDR. Step length is closely connected with activity. Faster movement usually means longer steps. Even the step length of the same person varies from step to step. Last, the heading angle, i.e., the moving direction, of the pedestrian needs to be calculated. Conventionally, gyroscopes and/or magnetometers are used for the heading estimation [3], [4]. However, magnetometers are known to suffer from the errors caused by ferromagnetic metal elements in buildings.

In order to do PDR, many research teams have been using Inertial Measurement Unit (IMU) consisting of accelerometers, gyroscopes and in some cases also magnetometers. Conventionally more expensive IMU provide more accurate results. In past few years, there have been tendency to use low-cost sensors for personal navigation. Embedded appropriate sensors in smartphone allow them to be used as a suitable device for the PDR. One advantage is, that almost everybody owns smartphone, but on the other hand their accuracy might not be as high as needed. As mentioned, GNSS is insufficient in urban environment. One of the possible solution for open-space area was presented in [5] and [6] where GNSS was combined with PDR. IMU can be attached to different body parts. One major class is waist or torso-mounted IMU [7]. In addition, there are helmet-mounted [8] and foot-mounted PDR systems [9]. Usually the foot-mounted systems are more accurate, e.g. in [10] the position error was below 5% of travelled distance for indoor and outdoor environment. Nevertheless, MEMS sensors alone cannot provide accurate information because of many negative effects, e.g., bias, thermal noise, 1/f noise or non-orthogonality of axis. Thus one option is to combine them with different localization methods. For example, in [11], [12], [13] and [14] combination of inertial sensors with Wi-Fi for handheld device was presented, similar combining method with UWB can be found in [15] and in [16] PDR and light sensor in smartphone were combined. Selecting the optimal filter plays also an important role. Example of system combining multiple sources of position information using Kalman Filter (KF) can be found in [13] and [17]. In addition, combination of multiple smartphone sensors including magnetometer, gyroscope, accelerometer and pressure sensor is used in [18]. While KF one of the most often used fusion techniques, it is not applicable in all the situations. For example, Particle Filter (PF) is found to be more suitable for a map matching problems [19], [20].

In the prior art, use of smartphone IMU sensors for the PDR is described in [17], and [21]. In [22] estimation of smartphones position and orientation is presented. Different walking scenarios like holding smartphone in hand, in front of

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face, facing ear, smartphone in trouser pocket, in bag and smartphone in swinging hand were discussed. In [23] a novel finite state machine based step detection technique is presented for more precise personal navigation with foot-mounted IMU. Compared to foot-mounted systems, the step detection algorithms in waist-mounted systems are more similar to the algorithms used in handheld systems. One solution with the waist-mounted IMU is presented in [7]. Step length calculation by using simple harmonic motion by using Pythagoras theorem is presented in [24]. Activity classification, such as walking and going up and down the stairs, is defined in [25]. Adaptive Pedestrian Activity Classification (PAC) can be found in [26], which classifies two basic states, standing and walking. It is able to add two additional activities, moving up and down. After the step detection and the step length estimation, heading angle has to be calculated. In [4] improved heading estimation is discussed, it uses correlation between gyroscope and magnetometer. Different way of heading angle calculation is in [3]. In the paper calculation has been done by using Quaternions. Both mentioned works bring precise calculation of heading angle for PDR. Heading angle calculation by using magnetometer is described in [27]. In that work, also a new reduction method for heading estimation error is presented.

In this paper, we compare off-the-shelf smartphone and more accurate and expensive Xsens IMU. The chosen path was walked while holding both devices at the same time in hand. In the first case, the estimated path was calculated from measured data without any external aiding information. Then we also used PF with map constraints for path estimation. Results were compared with the reference path and errors were calculated by using cross track method.

The rest of the paper is organized as follows. Section II describes PDR. The principle of PF is discussed in Section III. Experimental setup and results can be found in Sections IV and V. Conclusions are given in Section VI.

II. Pedestrian Dead Reckoning

A. Step Detection

First in PDR, we need to detect the steps. To detect steps of a pedestrian, accelerometer data was used. The significant pattern of the step is in the vertical axis relative to the ground. In order to get the vertical component of the acceleration, we need to track the attitude of the measurement device accurately. However, this is not always possible due to limited quality of sensors. Therefore, usually norm of acceleration is used. Norm of acceleration $a(t)$ in time t is calculated as

$$a(t)=\sqrt{a_x^2(t)+a_y^2(t)+a_z^2(t)}-g \qquad (1)$$

where g represents gravitational acceleration and a_x, a_y, a_z represents measured acceleration in all three axis of accelerometer [4]. After calculation of the acceleration norm, step detection method can be applied. In this paper, zero crossing method is used. Other options are peak detection or frequency analysis of signal [2]. The norm of acceleration is shown in Fig. 1. Red circles denote detected steps.

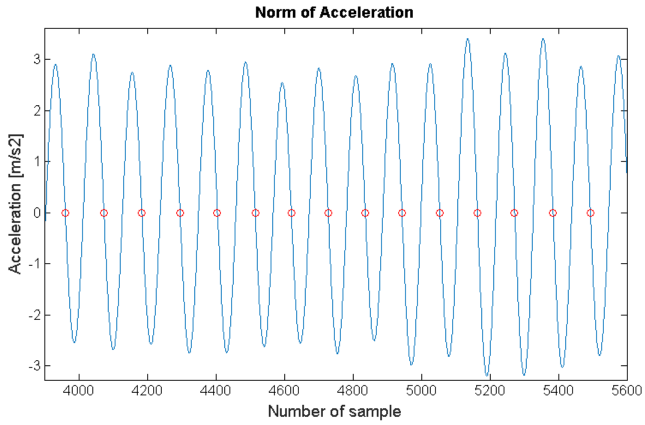

Fig. 1. Norm acceleration and zero crossing detection.

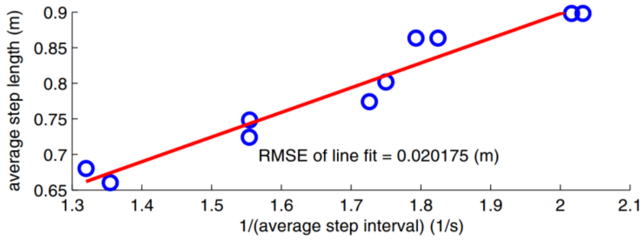

Fig. 2. Step length [19].

We used zero crossing method with time condition. New step can be detected only, if time difference between two consecutive zero crossings was more than 0.5 s. This condition provides protection against detection mistakes which may otherwise occur.

B. Step Length and Activity

Basically each step has a different length because of many factors, e.g., age, gender or height of pedestrian. Younger people, men and tall people generally make longer steps. The length of step also varies during the walking. One option for step length estimation is presented in [4]. Fig. 2 shows the dependency of step length in relation to frequency. This information can be used in activity classification [6], [19].

However, in this paper constant step length of 0.75 m has been used. We assumed only two motion states walking and standing. Two thresholds were set in positive and negative part of the signal. If the signal crosses both thresholds step is accepted which indicate walking. In remaining cases standing was detected.

C. Heading Estimation

The attitude estimation of smartphone relative to the global frame can be done by integrating angular velocity measured by gyroscope in body frame

$$\omega_b(t)=\left(\omega_x(t),\omega_y(t),\omega_z(t)\right) \qquad (2)$$

where ω_x, ω_y, and ω_z are angular rotations in body frame for all axis. One way to present the attitude of the IMU is to use Direction cosine matrix (DCM). DCM is 3-by-3 rotation matrix

$$\mathbf{C} = \begin{bmatrix} \cos\theta\cos\psi & \cos\theta\sin\psi & -\sin\theta \\ \sin\varphi\sin\theta\cos\psi - \cos\varphi\sin\psi & \sin\varphi\sin\theta\sin\psi + \cos\varphi\cos\psi & \sin\varphi\cos\theta \\ \cos\varphi\sin\theta\cos\psi + \sin\varphi\sin\psi & \cos\varphi\sin\theta\sin\psi - \sin\varphi\sin\psi & \cos\varphi\cos\theta \end{bmatrix} \tag{3}$$

where symbols ϕ, θ, ψ represent Euler angles roll, pitch and yaw. Rotation matrix must be updated all the time for tracking IMU orientation. Updated matrix $C(t+\Delta t)$ can be written as

$$\mathbf{C}(t+\Delta t) = \mathbf{C}(t)\left(\mathbf{I} + \frac{\sin\sigma}{\sigma}\mathbf{B} + \frac{1-\cos\sigma}{\sigma^2}\mathbf{B}^2\right), \tag{4}$$

where Δt is sampling interval and

$$\mathbf{B} = \begin{bmatrix} 0 & -\omega_z\Delta t & \omega_y\Delta t \\ \omega_z\Delta t & 0 & -\omega_x\Delta t \\ -\omega_y\Delta t & \omega_x\Delta t & 0 \end{bmatrix}, \tag{5}$$

$$\sigma = \left|\Delta t\,\omega_b\right|, \tag{6}$$

and $\boldsymbol{I}$ is 3-by-3 identity matrix. After that, we are able to calculate heading angle, i.e., yaw angle, Ψ from updated rotation matrix [28]

$$\psi = \arctan_2\left(C_{2,1}, C_{1,1}\right). \tag{7}$$

After step detection and heading angle estimation, position can be calculated as

$$\begin{bmatrix} P_{E_k} \\ P_{N_k} \end{bmatrix} = \begin{bmatrix} P_{E_{k-1}} + l_k \sin(\psi_k) \\ P_{N_{k-1}} + l_k \cos(\psi_k) \end{bmatrix}, \tag{8}$$

where P_{E_k} and P_{N_k} represent east and north position, l_k is the step length and ψ_k is the heading angle at moment k. Simple scheme is shown in Fig. 3.

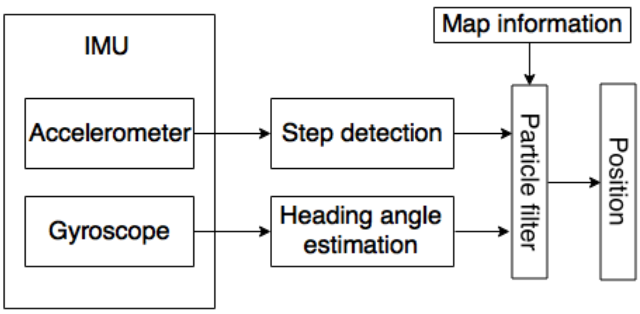

Fig. 3. Scheme of system working

Fig. 4. Measurement equipment

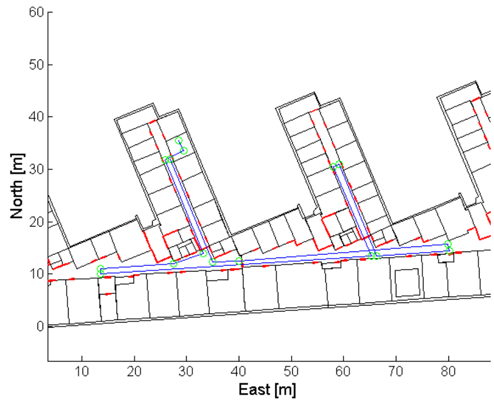

Fig. 5. .Reference Path.

III. Particle Filter

To combine various sources of information optimally, Bayesian filters can be used. However, this method cannot be used if measurement model is nonlinear. A popular approximation method of the Bayesian filters is called particle filter (PF). This method approximates the posterior state distribution by using particles. Representation of the particles as individual points gives advantage with map combination process, known as map-matching.

Similarly to KF, PF has both prediction and update steps. First, particles $x^{(k)}, k = 1, \ldots, N$, are drawn from proposal distribution in a time moment t.

$$x_t^{(k)} \approx \pi\left(x_t^{(k)} \middle| x_{t-1}^{(k)}, y_{1\ldots t-1}\right), \tag{9}$$

where $y_{1\ldots t-1}$ represents measurements one moment before t. We assume that states establish Markov model. This means that the current state x_t depends only on the previous state x_{t-1}. During the update phase, weights are recalculated according to the observation likelihood as

$$w_i^k = w_{i-1}^k \frac{p\left(y_t \middle| x_t^{(k)}\right) p\left(x_t^{(k)} \middle| x_{t-1}^{(k)}\right)}{q\left(x_t^{(k)} \middle| x_{t-1}^{(k)}, y_i\right)}. \tag{10}$$

After update step weights are normalized. During running of the particle filter there will be few particles, which will get all calculated weights. Propagation particles with very low weight negatively affect posterior distribution. This problem is known as degradation, and can be avoided by resampling [29], [30]. Different resampling method can be found in [31]

IV. EXPERIMENTAL SETUP

Measurements were done by using two different IMUs. The first one is low-cost Samsung Galaxy S6 Edge's IMU MPU 6500 and the second is more expensive Xsens IMU shown in Fig. 4. The reference path of walking is shown in Fig. 5. The route is represented with blue lines, and red lines represent crossing areas e.g. doors. The route of both devices should be the same. Data from the smartphone was measured by using Androsensor application and sampling frequency was set to 200 Hz. For measuring Xsens IMU data, MATLAB script was created. Sampling frequency was set to 40 Hz. As mentioned before, frequency of walking is somewhere around 2 Hz and in both cases step length was set as constant 0.75 m. Step detection and heading estimation were done as described in Section II A and II C.

Quantifying errors is a complex problem. In this paper cross track method has been used. Whole path has been divided into parts and has been compared with the reference path's straight lines in Fig. 5. Green circles represent the start and end points of each part. In order to find the location in the reference path, we searched the locations of turns from the heading data. This can be seen from Fig. 6. where peaks denotes turns. However, more turns were detected than were actually made Therefore it required manual correction.

After splitting path into smaller sections, each reference part has it´s own travelled path segment. Segments consist of detected steps and each step has coordinates in 2D. Distance between point and line has been calculated by

$$D = \frac{\left|(y_2 - y_1)x_0 - (x_2 - x_1)y_0 + x_2 y_1 - y_2 x_1\right|}{\sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2}} \tag{11}$$

where $P_1(x_1, y_2)$, $P_2(x_1, y_2)$ denotes starting and ending point of the lane, and (x_0, y_0) represent coordinates of the point.

V. RESULTS

Measurements were done with both devices at the same time. Both devices were held in hand in the same orientation. Reference path is shown in Fig. 5. Path measured by smartphone and Xsens IMU without using the filter are compared with the reference path and can be seen in Fig. 7. At first sight, Xsens data seem more accurate than smartphone data. Most errors could occur while turning. As mentioned before, both devices were held in hand, which can cause tilt in horizontal axes and it can be seen in Fig. 8 for Xsens and in Fig. 9 for smartphone.

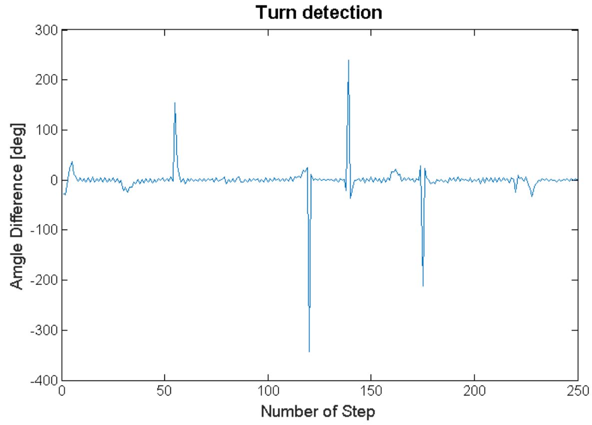

Fig. 6. Heading angle turn detection.

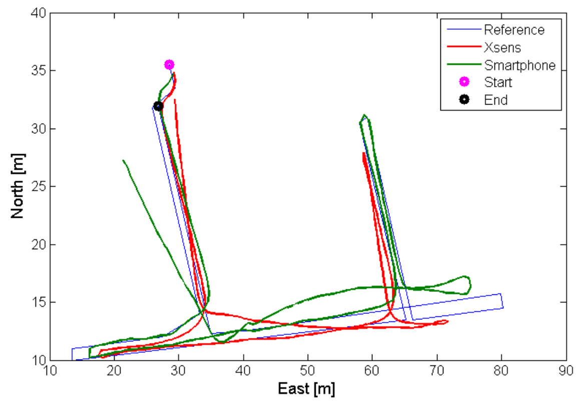

Fig. 7. Path measured by Smartphone and Xsens IMU.

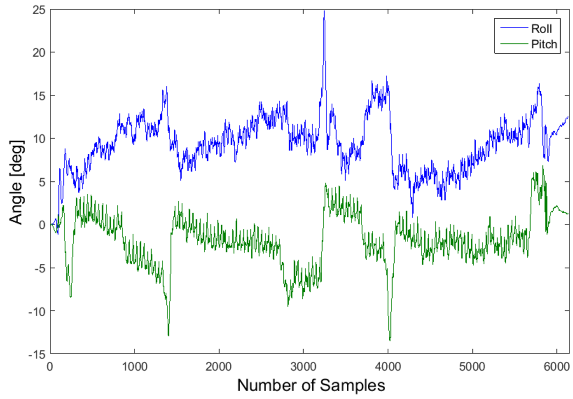

Fig. 8. Tilt of Xsens IMU in x and y axis.

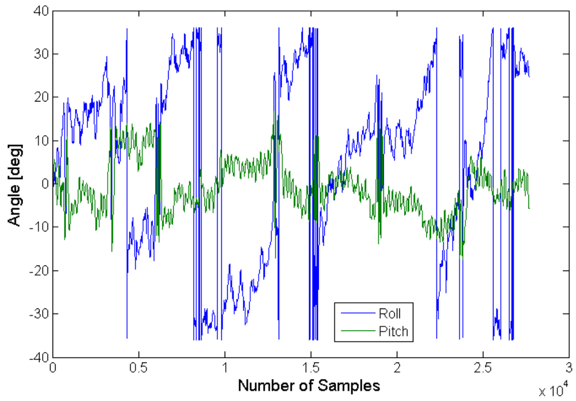

Fig. 9. Tilt of smartphone IMU in x and y axis.

Particle filter has been used as a map matching method for improving accuracy. Starting position has been set manually and 200 particles have been calculated around this position in all directions because of unknown initial heading, which can be seen in Fig. 10. Weights of the particles crossing the walls were set to zero. When the number of particles was less than N/5 the resampling phase started.

The wlked path was approximately 185 m and user made 245 steps. 246 steps were detected according to smartphone data and 250 steps according to Xsens data. Error in step detection may be caused by unexpected shaking while opening doors.

The final path was calculated from all particles as their weighted average. However, this is not the optimal method, because obstacles, such as small corridors, can cause multimodal distribution where particles are distributed in many different clusters. Thus, the final result is average of those clusters, which obviously yields in false estimate.

In Fig. 11 path calculated from Smartphone is shown. Here we can see previously mentioned problem. In some locations there are miss-crossed areas. Similar issue can be observed in Fig. 12 with xsens. Blue lines in both figures denote calculated path by Particle filter.

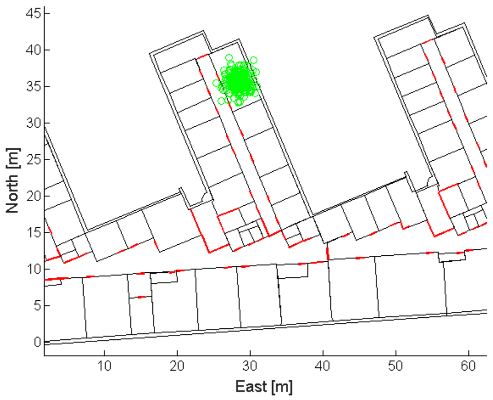

Fig. 10. Initial state.

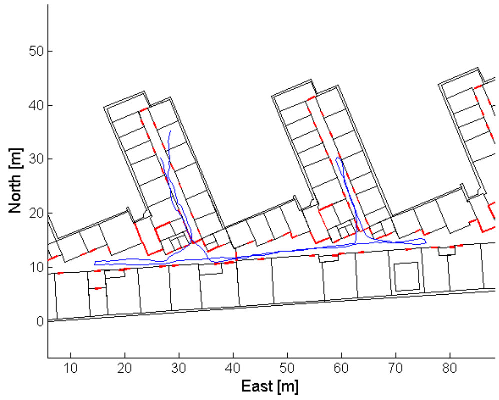

Fig. 11. Path after filtering calculated from Smartphone data.

TABLE I. PATH ERRORS

	Device			
	Smartphone		***Xsens***	
Location Error [m]	***With PF***	***Without PF***	***With PF***	***Without PF***
Min	0.001	0.0001	0.0036	0.0199
Max	6.3538	6.7217	5.7058	8.6054
Average	0.6577	1.2643	0.7097	0.7875

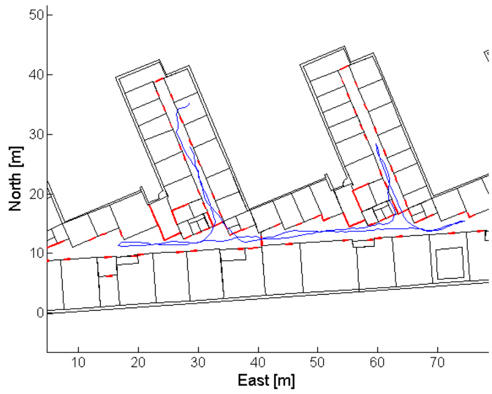

Fig. 12. Path after filtering calculated from Xsens data.

Cross track method described in Section V is used for error calculation. Errors were calculated for each step separately and results can be seen in Table I.

From Table I can be seen that usage of particle filter improves accuracy of both devices. As we assumed, data measured by Xsens were more accurate with average error of 0.7875 m without PF. While accuracy improvement for Xsens was 0.08 m, in smartphone´s case it was more than 0.6 m. That means particle filter can limit the error growth. In order to better understand differences of the positioning accuracy achieved by both devices, cumulative distribution functions (CDF) of localization errors are compared in following figures. In Fig. 13 localization errors achieved by smartphone is depicted.

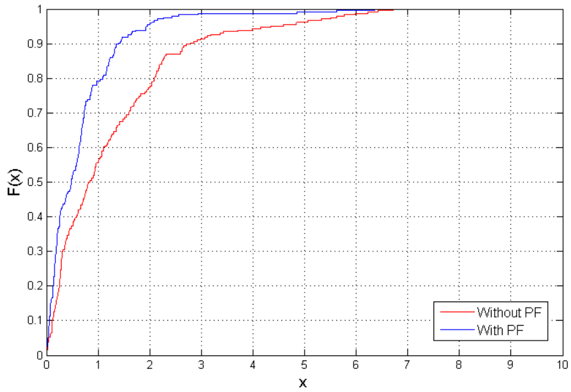

Fig. 13. CDF of Smartphone errors

From the figure above it can be seen that implementation of PF significantly decreases the localization error. It can be seen that median error is less than 0.485 m with PF. 90 % of estimation errors are less than 2.836 m without PF, and 1.437 m respectively with PF. Generally, the error with PF is half of the error without PF. In the Fig. 14 localization errors achieved by using Xsens is shown. The difference between data achieved by with/without PF is not so significant compared to smartphone results. It confirmed our assumption that the accuracy of Xsens IMU is better. Median error is almost the same, i.e., 0.6 m. 90 % of the estimation errors are less than 1.898 m without PF and 1.483 m for data obtained with PF respectively. Positive impact of PF on accuracy is evident in part of bigger errors. Finally, it can be concluded that the positioning errors achieved after filtering implementation is very similar.

VI. Conclusion

Quality of smartphone inertial sensors has been rapidly increased over the past few years. A device, primarily assigned for calling and texting, has become a versatile gadget mostly because of multiple embedded sensors. The fact that these sensors are available, makes smartphones suitable devices for indoor navigation.

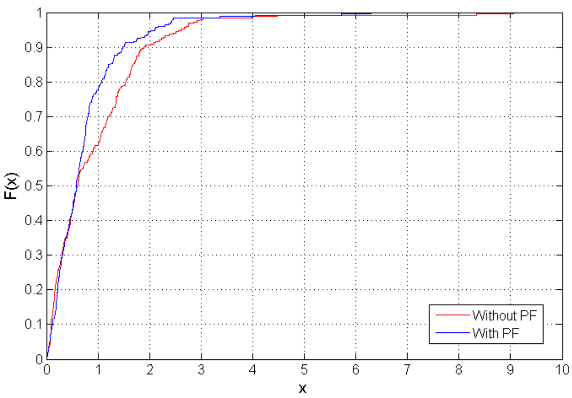

Fig. 14. CDF of Xsens errors

This paper presented PDR in indoor environment using smartphone sensors. Data measured by smartphone was compared to Xsens IMU. The measurements were done by using Androsensor application in smartphone and data from Xsens was collected by prepared MATLAB script in real time. The noted fact that low-cost sensors cannot provide accurate results alone was demonstrated in the results. From average error of 0.7875 meters with Xsens and 1.2643 meters with smartphone without PF, the accuracy was improved up to 0.7 meters with both sensors using PF. Even though PF has lower effect to improve accuracy compared to Xsens, its effect will be more significant in longer measurement. In addition, absence of PF causes that the error will grow rapidly without limitations.

It has to be noted that even if we are talking about low-cost sensors, Samsung Galaxy S6 is equipped with MPU6500, which can be considered relatively accurate. There are still many devices in middle and low class, which are equipped with various types of less accurate older sensors. Therefore, not all smartphones are suitable for indoor navigation yet.

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