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Robust Pedestrian Localization in Indoor Environments with an IMU Aided TDoA System

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***Abstract*—Pedestrian localization systems require the knowledge of a user's position for manifold applications in indoor and outdoor environments. For this purpose several methods can be used, such as a Global Navigation Satellite System (GNSS). Since GNSS are not available in indoor environments or deep street canyons other techniques have to be used. This could be a time based or signal strength based radio localization system. In this paper a Time Difference of Arrival (TDoA) system is used and combined with a low cost accelerometer and gyroscope. Since the localization device is free mountable at the user's body, the raw data of the gyroscope must be rotated in a global frame. Therefore the accelerometer is used to compute the rotation angles in relation to the earth's gravity. The data of the accelerometer is also used for a step detection and a step length estimation as well. To fuse the different measurements an Extended Kalman Filter (EKF) is employed. While the system is initialized the orientation of the user is not available. Therefore an initial phase is prepended where a reduced model is used. In this phase the orientation has to develop while the user is moving. The duration of the phase is dynamic, depending on the quality of the TDoA measurements. Once the initial phase is passed the complete model is used. To evaluate the introduced algorithm experimental results in different environments are presented.**

***Index Terms*—Time Difference of Arrival; Pedestrian Localization; Indoor; Inertial Measurement Unit; Extended Kalman Filter**

I. Introduction

Localization of human operators is the basis of any Location-Based Service (LBS). LBS provide information or services with respect to the current position. There are many existing applications such as restaurant finders or museum guides, which provide information about an exhibit or lead the way to a certain point of interest. Of course there is a need of an accurate localization in other domains, for example in logistics [1], safety applications or in the field of Ambient Assisted Living (AAL).

Outside of buildings Global Navigation Satellite Systems (GNSS), such as the Global Positioning System (GPS) or the European equivalent Galileo, are well suited to solve the positioning problem. There are many applications like car navigation systems, training support for runners and LBS on smartphones as well. In those applications GNSS, due to the accuracy of many meters, are often combined with other sensors. For example an Inertial Navigation Systems (INS), which measures the users steps and his orientation, or wheel encoders in cars [2] can be used. But inertial techniques need an initial position and cannot provide a long term stability of the position. If the user is in an indoor environment or a deep street canyon where GNSS information is not available over a long time period, the system supplies incorrect or no results. In such environments other techniques are needed to compute the user's position. In this paper we propose a Wireless Sensor Network (WSN) combined with an IMU for the localization. The WSN consists of stationary anchor nodes with prior known positions and mobile devices, which are attached to the users body [3].

In order to estimate a user's position in a WSN there are several techniques to accomplish this goal. An easy way to compute the position is to use the Received Signal Strength (RSS). Most radio receivers in a wireless system have the ability to measure the signal strength. This signal strength can be translated to a distance by using a path loss model. Another method is the use of a radio map. Here an offline phase is performed to take RSS measurements at specified points with known positions and stored in a map. In an following online phase the current measured RSS values of the user are compared to the saved ones in the map. Due to this relation a user can be localized [4].

Angle of Arrival (AoA) is a different method, which localizes users by measuring the direction of the incoming signal. For this purpose special antenna arrays are needed. If some measurements to different anchors are available the current position can be computed using triangulation.

Apart to the already introduced techniques, there are a couple of methods based on the signals Time of Flight (ToF). One of them is to measure the Time of Arrival (ToA). While using this method the clocks of all participants must be precisely synchronized. Due to the knowledge of the signals velocity the position can be computed by trilateration. If the synchronization between the anchors and the mobile devices is not possible, the Roundtrip Time of Flight (RToF) can be used instead. Here the system measures the signals flight duration from the mobile device to the anchor and the other way round. This eliminates the clock error but increases the duration per distance measurement. Another method is to measure the Time Difference of Arrival (TDoA). In this approach only the anchors have to be synchronized. Basically there are a few methods to derive TDoA measurements. In this paper the so

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called uplink TDoA is used. Here the tag broadcasts a signal, which is processed on the anchor nodes. Using multilateration the resulting time differences can be translated to a position.

A more detailed overview of the presented methods and their applications is given in [5].

In this paper the used uplink TDoA system is supported by an accelerometer and a gyroscope to estimate a person's position and velocity. To deal with the noisy measurements of the sensors an Extended Kalman Filter (EKF) is employed. Furthermore the tag shall be free mountable somewhere to the user's body.

II. Related Work

Due to the increasing demand for indoor positioning systems, wireless localization has been an important research field in the past years. Many published papers deal with different kinds of localization techniques in GNSS and WSN. In [4] a RSS fingerprinting algorithm is presented, which uses a particle filter to estimate the position from a radio map. Because of the limited accuracy of RSS based methods it is useful to make combinations with other techniques. So [6] and [7] use algorithms to fuse ToA respectively TDoA measurements with the signal strength. Disadvantage of the algorithm used in [7] is the non-observance of multipath propagations. Other papers deal with the combination of wireless localization and INS. In [8] a system is presented, which fuses RSS measurements with a step detection, step length and orientation estimation. This extension increases the accuracy of the system many times over. Similar observations were made in [9] where the authors used a combined UWB/INS System.

Due to the popularity of smartphones, which are mostly well equipped with GPS, WiFi and inertial sensors, there are many researchers working on such locating systems as presented in [10] or [11].

In many applications it is useful to combine indoor with outdoor localization techniques as the authors did in [12]. Here GPS and RFID are used to achieve a seamless transition between indoor and outdoor areas.

III. System Overview

To perform the experimental results the nanoPAL RTLS Toolbox provided by Nanotron Technologies is used [13]. The commercial available system confirms the IEEE 802.15.4a standard and works in the 2.4 GHz ISM band. IEEE 802.15.4a defines Chirp Spread Spectrum (CSS), which is used by the toolbox, and Ultra Wide Band (UWB) for measuring distances. The MEMS accelerometer BMA150 by Bosch with an output noise of $0.5\,{}^{\mathrm{mg}}/\sqrt{Hz}$ is used to detect steps and to make the additional step length estimation. To estimate the users walking direction the MEMS gyroscope L3G4200D by STMicroelectronics with a noise of $0.5\,{}^{\mathrm{dps}}/\sqrt{Hz}$ is utilized. Both MEMS sensors are acquirable for less than 10 $, depending on the purchase quantity.

The structure of the whole filter process with the different preprocessing steps and the dependencies between each other is shown in figure 1.

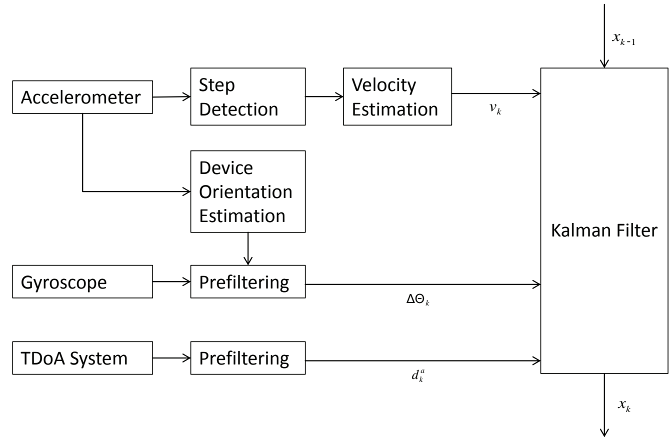

Fig. 1: System overview

The data of the 3-axis accelerometer is used to detect steps and to determine the orientation of the device. Once the user is in motion and steps are detected, the velocity is estimated to use it in the EKF. The orientation of the mobile device is utilized to correct the measurements of the 3-axis gyroscope, which has to be translated from a local to a global frame. Since the TDoA measurements are affected by different error sources such as multipath propagations and fading, they must be prefiltered before they are processed in the Kalman Filter.

IV. Prefilter

The raw measurements of the different sensors are not usable due to the vibrations during the step and the unknown tag orientation, in case of the accelerometer and gyroscope, or influenced by external error sources like Non-line-of-Sight (NLOS). Therefore separate prefilters are implemented to make the sensors useful and more accurate.

A. Accelerometer

While the device is body-mounted, the steps overlay the forward acceleration of the pedestrian within the measured signal. To deal with this problem, the steps of the person are detected with a mixed threshold and zero crossing based algorithm as it is used for example in [14]. In this paper the magnitude of the signal is used for the detection. While the signal crosses a defined threshold and passes zero for two times it is assumed that the user is moving. Furthermore if a step is detected a step length estimation is employed to make the algorithm more accurate. The used estimation was first presented in [15], where the covered distance is approximated by:

$$d \approx i\sqrt[4]{A_{max} - A_{min}}. \tag{1}$$

A_{max} and A_{min} are the maximum respectively the minimum value of the acceleration within the step, while i is a scaling factor to handle different walking behaviors and leg lengths. The formula is based on the principle of an inverse pendulum. After the step length is estimated the velocity is calculated with respect to the known duration for the step:

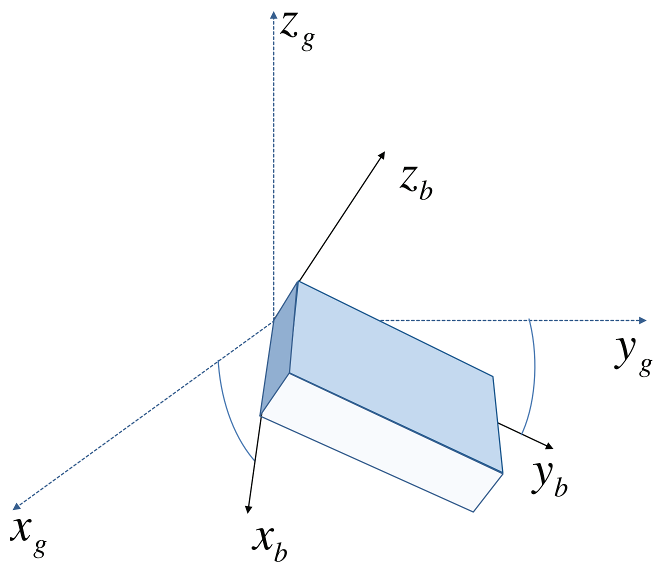

Fig. 2: Device to body coordinate frame transformation

$$v = d(t_2 - t_1) \tag{2}$$

Where v is the velocity and $t_2 - t_1$ indicates the duration from a first step at t_1 to a second step at t_2. If there is no new step measured within a short period, with respect to the walking frequency, t_1 has to be measured again.

B. Gyroscope

Since the sensor tag is free mountable to the body it is not clear in which orientation the three axis gyroscope is located. Therefore the accelerometer is used to calculate rotation angles to make a transition between the tag and the body coordinate system as it is shown in figure 2.

The local body frame denoted by $(x_b\ y_b\ z_b)$ has its origin in the tag mounted at the user's body. Since the local changings in the orientation must be translated into a global frame, which is fixed to the gravity of earth, denoted by $(x_g\ y_g\ z_g)$, the rotation angles α and β are calculated over the geometric relations as the authors did in [16]. α and β are computed with respect to the measured earth's gravity $|a|$ as follows:

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2}, \tag{3}$$

$$\alpha = \arcsin\left(\frac{a_x}{|a|}\right), \tag{4}$$

$$\beta = \arcsin\left(\frac{a_y}{|a|}\right). \tag{5}$$

Therefore the tag has to be in a neutral position and it is obtained that the gravity of earth g approximately correspond to the measured signal $|a|$:

$$g \approx |a| = \sqrt{a_x^2 + a_y^2 + a_z^2}. \tag{6}$$

Once the rotation angles are computed the rotational speed measured by the gyroscope in the body frame $\boldsymbol{\omega^b}$ can be calculated to the global ones $\boldsymbol{\omega^g}$:

$$\boldsymbol{\omega^g} = \begin{pmatrix} \cos\alpha & \sin\alpha\sin\beta & \sin\alpha\cos\beta \\ 0 & \cos\beta & -\sin\beta \\ -\sin\alpha & \cos\alpha\sin\beta & \cos\alpha\cos\beta \end{pmatrix} \boldsymbol{\omega^b} \tag{7}$$

While even straight movements of a person have an influence on the turning rate and because of the high drift of low cost gyroscopes another prefilter is needed. To address these points only high turning rates are passed through. Otherwise in case of slow turnings during the walk the changes in the orientation has to be detected by the TDoA measurements.

C. TDoA

One problem while using a TDoA system is to detect multipath propagations and Non-line-of-Sight (NLOS) measurements. Since there are two time measurements in every computed difference, it is difficult to assign the corrupted measurement to a single anchor. In [17] several methods, which handle those situations and discard defective measurements, are presented. Since we use a system where each anchor node consists of two independent chips and antennas, we are able to select the better TDoA value without losing information. For every anchor node it is obtained that if one of the two measurements at one anchor is significant smaller, it is assumed that the other is affected by a multipath propagation. The threshold depends on the size of the environment, but we found that values between 0.1m in smaller areas and 0.5m in larger areas work well. Furthermore it is not possible that a TDoA measurement is larger than the ToF measurement between the involved anchor nodes A^1 and A^2 with the positions $p(A^1)$ and $p(A^2)$:

$$|\boldsymbol{d}_{1,2}| \leq \left\|p(A^1) - p(A^2)\right\| - b\ . \tag{8}$$

A value b is subtracted which decreases the distance between the anchors. Due to the geometry of the hyperbolas, when they are located near an anchor even small errors in the measurement cause large errors in the position estimate. Measurements which are related to one of these two facts are completely discarded and not used in the EKF.

V. Extended Kalman Filter

The Kalman Filter, which was first introduced in [18], is a recursive state estimator of a linear dynamic system. The filter handles incomplete and noisy measurement-data by minimizing the mean squared error. If the state transition or the measurement model is modeled by non-linear equations, the Extended Kalman Filter can be used instead [19]. The EKF linearizes the non-linear system by using a first order Taylor expansion. The non-linear function $\boldsymbol{f}$ translates the state vector $\boldsymbol{x}$ at time step $k-1$ to the next time step k, while the function $\boldsymbol{h}$ relates the current state to the measurement $\boldsymbol{z}_k$:

$$\boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{x}_{k-1}, \boldsymbol{u}_k, \boldsymbol{\omega}_k), \tag{9}$$

$$z_k = h(x_k) + \nu_k. \tag{10}$$

The random variables ω_k and ν_k represent the noise of the state transition and the measurement. They are assumed to be white, mutually independent and normally distributed with covariances Q_k and R_k respectively.

The initial position is computed by a multilateration least squares algorithm which is presented in [20]. Since there is no option to obtain a global direction with the given sensors, the orientation has to be derived from the movements of the pedestrian. Therefore the orientation is not explicit contained in the state vector x_k, but it is build as follows:

$$x_k = \begin{bmatrix} x_k & y_k & v_{x,k} & v_{y,k} \end{bmatrix}^T. \tag{11}$$

Where x_k and y_k represent the position while $v_{x,k}$ and $v_{y,k}$ denote the velocities in x respectively in y direction. The advantage of this given state vector is, that there is no initial orientation needed but it is contained implicit in the both velocities, which grow while the user is walking. To get an initial estimate of the orientation, at least five straight steps are used to develop the velocities. Therefore only the TDoA values are used in the measurement model during this initial phase. The length of this phase depends on the quality of the TDoA measurements. If they have a poor performance more steps are needed. As an indicator for the quality the residual values e_i during the steps are used:

$$e = \sum_{i=1}^{I} e_i \tag{12}$$

with

$$e_i = \sum_{a=1}^{A} (z_i^a - h(x_k)). \tag{13}$$

Where I is the number of all TDoA measurement series during five steps and A is the number of all measurements at time step k. If the residuum e is lower than a defined threshold τ the measurement model is switched to the complete one, including TDoA and velocity measurements:

$$e \leq \tau. \tag{14}$$

If e is higher, the first value e_1 is shifted out, such that a new step is needed to proof the measurement quality. Once the query is passed the velocities should be stable and the step detection is added to the model.

If the user is turning, the velocities are rotated by a simple rotation matrix. Therefore the control vector u_k contains the change in orientation measured by the gyroscope:

$$u_k = \Delta\Theta. \tag{15}$$

The state transition function from 9 is assumed to be linear in relation to the state vector, so it becomes as follows:

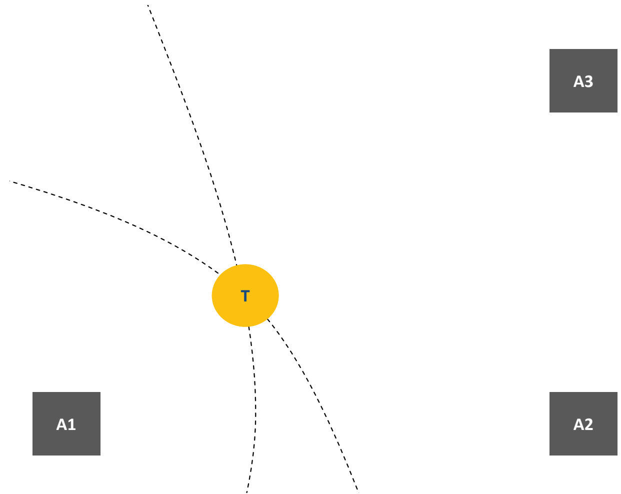

Fig. 3: Multilateration

$$\begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \end{bmatrix} = \begin{bmatrix} x_{k-1} + v_{x,k-1}dt + \epsilon_x \\ y_{k-1} + v_{y,k-1}dt + \epsilon_y \\ v_{x,k-1}(\cos(\Delta\Theta + \epsilon_\Theta) - \sin(\Delta\Theta + \epsilon_\Theta)) \\ v_{y,k-1}(\sin(\Delta\Theta + \epsilon_\Theta) + \cos(\Delta\Theta + \epsilon_\Theta)) \end{bmatrix} \tag{16}$$

Where ϵ_x, ϵ_y and ϵ_Θ represent the different noise components of ω_k. While the variances of x_k and y_k, σ_x respectively σ_y are constant values, the variances of $v_{x,k}$ and $v_{y,k}$ depend on the changing in the orientation, which variance $\sigma_{\Delta\Theta,k}$ is expressed as follows:

$$\sigma_{\Delta\Theta,k} = \alpha\Delta\Theta + c. \tag{17}$$

Where α is a scaling factor and c is a constant value. But because the relation is nonlinear the variances must be computed by the linearized matrix W_k:

$$\begin{bmatrix} \sigma_x \\ \sigma_y \\ \sigma_{vx,k} \\ \sigma_{vy,k} \end{bmatrix} = W_k Q_k W_k^T. \tag{18}$$

with

$$Q_k = \begin{bmatrix} \sigma_x & 0 & 0 \\ 0 & \sigma_y & 0 \\ 0 & 0 & \sigma_{\Delta\Theta,k} \end{bmatrix} \tag{19}$$

and

$$W_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -\sin(\Delta\Theta) - \cos(\Delta\Theta) \\ 0 & 0 & \cos(\Delta\Theta) - \sin(\Delta\Theta) \end{bmatrix}. \tag{20}$$

A. TDoA Measurement Model

In the update phase, the TDoA measurements are used to estimate the position. In an uplink TDoA system there are several fixed anchor nodes, with known positions and a well synchronized time basis. The anchors detect the signal and save the time, when the signal arrives. Afterwards all reached anchors forward the timestamp to a central server, where the timestamps are processed to time differences $t^{*,a}$ with respect to a reference anchor t^* as follows:

$$t^{*,a} = t^* - t^a. \tag{21}$$

Where t^* is the ToA measured at the reference anchor and t^a the one at the a^{th} anchor. The range differences d^a can be computed as follows:

$$\begin{aligned} d^a = c\,t^{*,a} =& \sqrt{(x_k - x^*)^2 + (y_k - y^*)^2 + (h_k - h^*)^2} - \\ & \sqrt{(x_k - x^a)^2 + (y_k - y^a)^2 + (h_k - h^a)^2} \end{aligned} \tag{22}$$

Where c is the propagation velocity of the signal, x_k, y_k and h_k denote the coordinates of the tag, x^*, y^* and h^* the reference anchor ones and x^a, y^a and h^a the coordinates at the a^{th} anchor. In this case the height of all participants is assumed to be constant. Each of these equations defines a hyperbola, which intersect in the position of the tag, if the measurements have no noise. This method is called multilateration and needs a least two hyperbolas to compute an unique position. Figure 3 shows a possible constellation of a minimal configuration in a TDoA network. In this case A1 is the reference anchor and A2 respectively A3 are the counterparts.

The corresponding measurement vector $\boldsymbol{z}_k^{TDoA}$ is defined as follows:

$$\boldsymbol{z}_k^{\mathrm{TDoA}} = \begin{bmatrix} d^1 & d^2 & \dots & d^A \end{bmatrix}^T + \boldsymbol{\nu}_k^{\mathrm{TDoA}}. \tag{23}$$

The measurement covariance $\boldsymbol{R}^{\mathrm{TDoA}}$ of the random variable $\boldsymbol{\nu}_k^{\mathrm{TDoA}}$ is assumed to be constant in every step k.

B. Velocity Measurement Model

The measurement model of the velocity, which is computed from the steps, is build quite simple:

$$\boldsymbol{z}_k^v = \sqrt{v_{x,k}^2 + v_{y,k}^2} + \boldsymbol{\nu}_k^v. \tag{24}$$

If there is no step detected, it is assumed that the user is not moving. So the measurement covariance $\boldsymbol{R}_k^v$ of the random variable $\boldsymbol{\nu}_k^v$ is assigned to a very small value in case of zero velocity and a higher value for non-zero velocities.

VI. Experimental Results

For evaluation purposes different test walks were performed in a empty hallway with a size of 25 m by 8 m. Here eight anchors were placed around the area in a rectangular setup. In order to communicate among each other and with a central server, every anchor is equipped with Ethernet. The central server provides the TDoA measurements to a locating engine. To ensure that different tag positions and different walking behaviors of the users work equally, three people performed the tests with three tag positions, one in the hand, in the back pocket and finally in the pocket of a shirt.

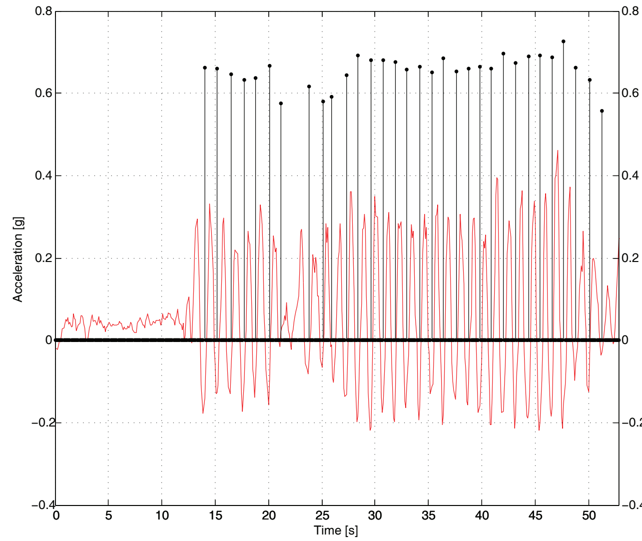

Fig. 4: Step Detection

A. Step Detection

The performance of the step detection is determined by the measured length the people travel in the test walks. All tests including all test people and tag positions were performed with a precalculated c from equation 1 of 0.9.
Figure 4 shows a part of a test walk where the tag was hold in the test persons hand. The red curve shows the signal of the accelerometer while the black stems indicate a detected step and its length as well. Here the person walked two straight lines with a 90 ° turn at 22 s where a small gap in the detected steps is located. The steps are steady with a length of slightly above 0.6 m.

In table I the overall accuracy of the step detection is shown divided by the tag position. While the test person carries the tag in his hand, the error has the lowest value. But if the tag is moved to the shirt pocked the error is increasing. This is because the tag is only loosely placed in the pocket, such that the accelerometer can poorly measure the acceleration of the step.
The overall error for all test walks is approximately 6 m on a traveled distance of 134 m, which correspond to a rate of 4.5 %.

	Error
Hand	3.67 m
Back pocket	5.12 m
Shirt pocket	9.06 m
Overall	5.96 m

TABLE I: Error of the estimated trajectory length with $i = 0.9$

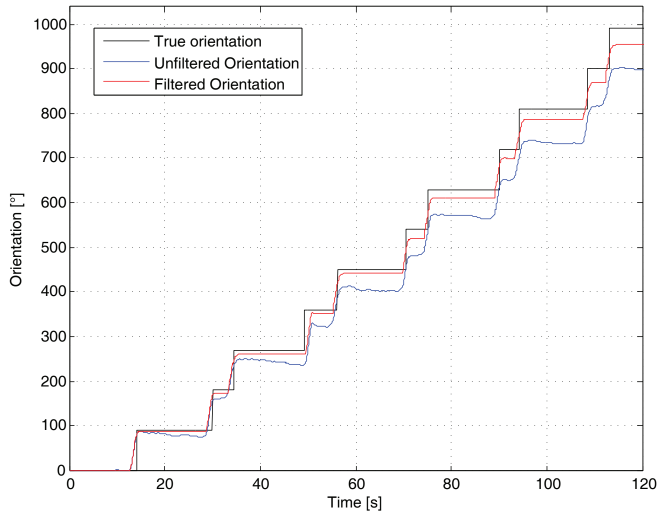

Fig. 5: Orientation estimation

B. Orientation Estimation

Figure 6 shows the difference of the filtered (red) and the unfiltered (blue) orientation. The walked path correspond to the one in the following figure 6. The path was walked three times, hence there are eleven 90 ° turns on the way. The orientation provided by the filter has a much higher accuracy with an error of 35.9 ° in this test case. By comparison, the unfiltered orientation has an error of 92.1 °.

The resulting estimation which is provided from the step detection and the orientation algorithm is shown in figure 6. This method is not applicable for long term localization applications because of the position error, which is increasing of time. Especially the error of estimated orientation has a poor influence on the accuracy.

C. Position Filter

Figure 7 shows the results of a normal test case where the tag was hold by a test person in his hand. The black curve denotes the real trajectory, while the green and the blue ones represent the estimations by the TDoA standalone version respectively the combined EKF. In the upper region the TDoA measurements were strongly influenced by multipath propagations of the radio signal. In this area the estimate of the standalone version has a poor performance, while the IMU aided version can bridge this time span.

Figure 8 shows a test case where the tag was placed in the test persons shirt pocket. Here the initial phase passed with a worse estimate of the position and the velocities, but after a short time the position is adjusted and the performance of the filter is getting better the longer the walk takes. The cumulative distribution function over all tests in figure 9 shows that the developed filter performs well. In ninety percent the combined EKF has an error of 1,7 m or lower while the TDoA version is located at 2,32 m.

Figure 10 shows the accuracy of the algorithm divided by different mounting positions of the tag. Here once again the test cases in which the tag was carried in the hand provide

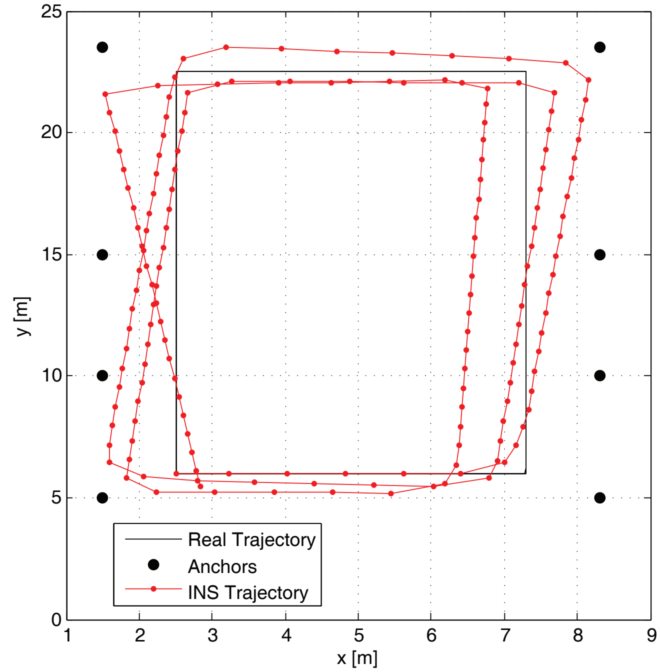

Fig. 6: Trajectory of the Inertial Navigation System

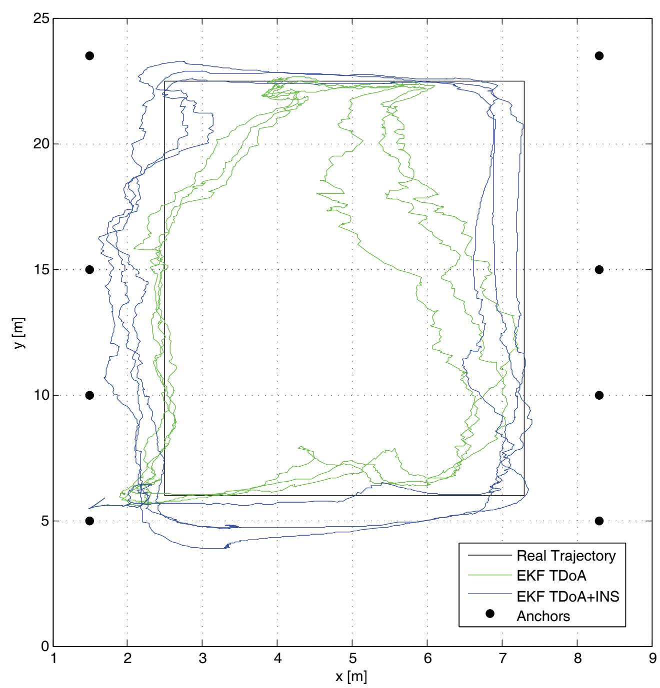

Fig. 7: Rectangle walk

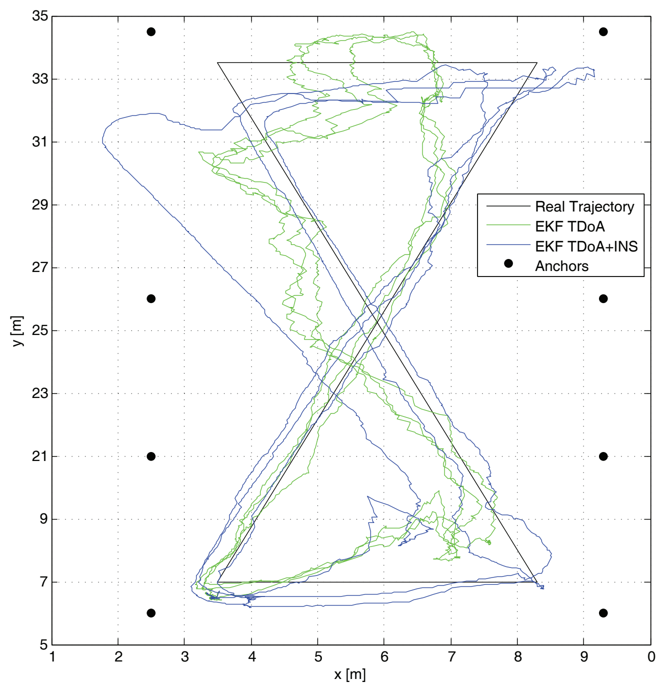

Fig. 8: X walk

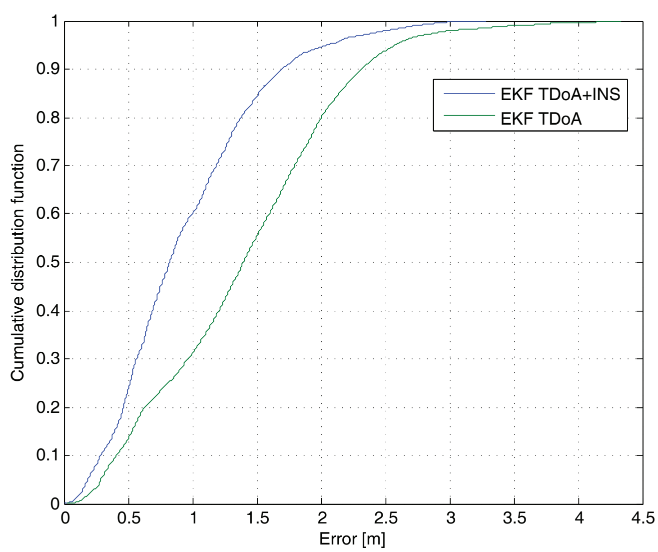

Fig. 9: Overall cumulative distribution function

the best results. Mainly in the upper figure part of 90 % to 100 % this mounting option performs better. The reason for this is, that the tag has in this position a better connectivity to the anchors with more line of sight conditions. The other tag positions cause much more multipath propagations because the test person shadows the radio signal with his body.

VII. Conclusion and Future Work

A robust and suitable algorithm for a localization system with low cost inertial sensors has been presented in this paper. It has been shown that the developed location algorithm in most test cases significantly increases the accuracy in relation

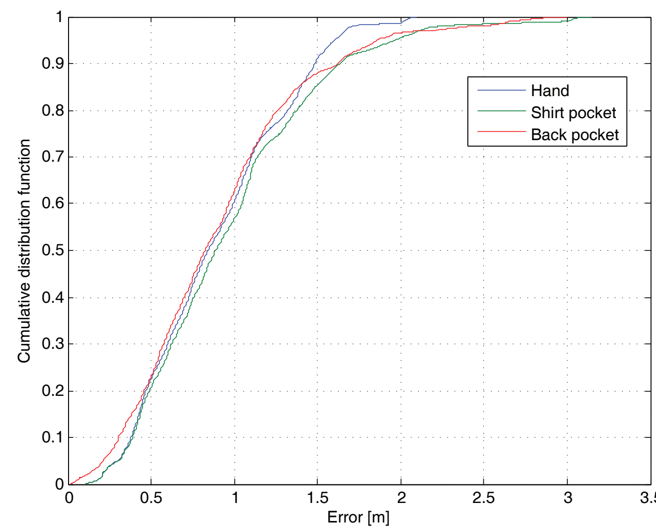

Fig. 10: Cumulative distribution function for different tag positions

to the stand alone TDoA version. It has been shown that the indicator for an entry point for the complete filter model works well, such that the orientation is always for the localization sufficient developed.
Only in case that the tag get out of place the algorithm could fail if a recalibration is not possible. Therefore other techniques must be developed to ensure that these situations are detected.

One of the desired application purposes is to use the system in salesrooms. In this environment it might be helpful to use map information in the localization algorithm to increase the accuracy once again. The map can be used to exclude impossible tracks through the store because of walls or other obstacles.

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