An Approach to Infrastructure-Independent Person Localization with an IEEE 802.15.4 WSN

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Abstract—**In this paper a new concept for an infrastructure independent approach to indoor person localization is outlined. It is proposed to deploy an ad-hoc wireless sensor network (WSN) by means of a pedestrian dead reckoning (PDR) unit. The deployed nodes are initialized with a PDR-determined position estimation. Furthermore, a subset of the nodes has a GPS connection and thus an accurate estimation of the own position. Within this infrastructure, persons that carry on-body sensor nodes can then be localized based on received signal strength (RSS) evaluation and extended Kalman filter (EKF) data fusion.**

An experimental setup with a 65 node ZigBee sensor network is described and the collected data are evaluated off-line. It is analyzed how an RSS person localization performs under experimental real-world conditions. The proposed approach results in a localization accuracy on the order of a couple of meters for realistic parameter settings. Initial experiments on node deployment and a simulative evaluation of the influence of biased anchor node position estimations are presented. It is concluded that the proposed system can obtain an accuracy on the order of 3 meters without necessitating map knowledge or previously deployed infrastructure. This accuracy is sufficient for a range of person localization applications.

Index Terms—**WSN, localization, RSS, pedestrian dead reckoning.**

I. Introduction

Ad-hoc localization of persons in unknown surroundings has been a topic of increasing interest in the past few years [1], [2]. A simple person localization system (PLS) that can be set up ad-hoc and that allows to track persons or objects in a previously unknown area/place could be used in a range of applications: firefighters that enter a burning building [3], police men that operate in between and within buildings or also medical personnel that manages a disaster site with hundreds of injured persons [4], are all in need of a system that can be set up fast and easily. Such a system could enable them to logistically coordinate large scale operations in unknown environments by providing localization information on the participants in the network [5], [3].

For this purpose a PLS does not only need to work in a lab environment under known conditions but it also has to deliver sufficiently accurate results under realistic conditions. The PLS has to work in both in- and outdoor environments and map knowledge about the deployment area or previously deployed infrastructure cannot be assumed.

Existing systems often do not fulfill these requirements: the Global Positioning System (GPS) has the fundamental problem of not working within buildings, WSN localization systems mostly require pre-deployed infrastructure to work properly and pedestrian dead reckoning (PDR) systems cannot provide long term stability. Although the upcoming ultra-wideband (UWB) real time location systems (RTLS) are expected to be a well-suited technology for indoor localization, current systems mostly require an extensive previous calibration, lack real-world evaluations and are still too expensive for a disposable usage [6], [7].

In this paper an approach to person localization in unknown environments is proposed where an ad-hoc infrastructure is deployed by means of a PDR unit. Within this infrastructure it is then possible to localize persons that carry sensor nodes.

A prototype implementation of a 65-node WSN is evaluated in an indoor field. The resulting localization accuracy if a PDR node deployment is assumed is assessed off-line for the collected data.

The remainder of this paper is organized as follows: In Section II the relevant state of the art in the fields of sensor network localization and PDR localization is outlined. In Section III the intended applications are analyzed and the resulting requirements are deduced. Based on these requirements the proposed solution concept is outlined. In Section IV the implemented experimental system that is used for the experimental evaluation of the proposed concept is described. In Section V the setup and results are presented. These results are then interpreted and a conclusion and an overview of the next development steps are given in Section VI and VII.

II. State of the Art

Indoor localization and location based services have been topics of great interest for several years now. Various works present the state of the art in the area and give insight into the different relevant research fields [1], [2], [8]. For the purpose of this paper the state of the art is categorized into the fields of sensor network localization with a focus on RSS, PDR, and hybrid approaches that combine the two fields.

The focus of this overview lies on systems that have been implemented for experimental evaluations and not only evaluated in simulations.

A. Sensor Network Localization

Applications of indoor real-time location systems (RTLS) can be found in various areas from industrial asset tracking to patient tracking in hospitals [9]. Evaluated techniques include the measurement of angle, time or strength of a received signal, or the time difference between the arrival times of physically different signals. It is usually assumed that at least some of the nodes of a network have known positions (anchor nodes).

After this measurement step it is then possible to estimate the positions of nodes with unknown positions (blind nodes) and/or to track mobile nodes.

As application fields for RTLS are omnipresent, some commercially available solutions have come up in the last years that make use of different measurement techniques and position estimation algorithms. In the research community, one of the best investigated localization principles is the evaluation of the signal strength of received radio packets (RSS). This is due to its availability on most modern radio chips.

Quite a few papers have been published that investigate localization based on RSS measurements. In [10] the authors propose to implement a system that allows to estimate the position of a mobile node upon comparison of recorded RSS values with reference values. These reference values have to be recorded in a precedent training phase. A comparable approach is presented in [11], where additionally information about the RSS history is evaluated. The authors claim to achieve an average localization accuracy of 1.3 *m*. In [12] a WiFi network positioning system for mobile nodes is presented that compares RSS values to an RSS database and also provides quite an accurate position estimation. All the presented systems manage to achieve good accuracy after a training phase for a specific environment of interest. Some more of these so-called fingerprinting techniques have been presented in other publications. However, the common shortcomings of such approaches is that they require a pre-installed infrastructure and a training phase and thus cannot be used in an ad-hoc manner.

Other approaches that try to calculate the corresponding distances from RSS values and then to localize with geometric or other techniques have been investigated. But they tend to be much more complicated and less accurate for indoor scenarios. In [13] the authors describe an outdoor experiment with 45 sensor nodes and achieve an accuracy of 4.1 *m*. The authors of [14] claim to achieve an accuracy of 50 *cm* by using a particle filter approach. Both of the described approaches however have not been evaluated for indoor scenarios. Also the user is required to know the positions of anchor nodes before being able to localize nodes.

For all of the cited approaches it is difficult to compare the published total accuracies as this is commonly a function of the number of used nodes per area and thus not on the same scale for different experiments.

There are a few publications about indoor RSS node localization but the experimental evaluation of the systems is mostly limited to single rooms or few rooms. To the knowledge of the authors there has not been done much work on practical evaluation of larger scale indoor localization systems based on RSS measurements. Also most of the published experiments are conducted under optimal circumstances, i.e., the node that is to be localized is usually carried in a way to allow for optimal omnidirectional communication (line of sight). It is the goal of this work to evaluate indoor person localization under real-world conditions, i.e., for a node that is carried in a trouser pocket for example or for anchor nodes that have a bias in their position estimation.

B. Pedestrian Dead Reckoning

With the recent technical improvements and price decline in the area of microelectromechanical systems-based inertial measurement units (MEMS-IMU), pedestrian dead reckoning has received more and more research interest in the last few years. The approach to estimate the current position based on a previously determined position by evaluating acceleration and gyro data from an IMU is implemented in a variety of inertial navigation systems, e.g., [15] - [24].

As the accuracy of common MEMS sensors is still too low to allow for reasonable accurate results through double integration of a 3-axis acceleration sensor and gyro evaluation for attitude estimation, most state of the art approaches make use of additional system knowledge to improve localization accuracy. This knowledge usually comes from analyzing recurring patterns in the human course of motion while walking. A popular approach is to mount the IMU on the foot of a person and to perform so-called zero velocity updates, i.e., recalibrate the velocity estimation from the acceleration integration to zero whenever the foot comes to rest on the ground [15], [16], [17], [18]. By using two IMUs, one on each foot of the pedestrian and thereby adding redundant sensor inputs, the results can be further improved [19].

The additional assumption that human trajectories are usually either straight or incorporate more or less distinct turns can be used to compensate the drift of gyro sensors and thus further improve the results of such approaches [20], [21]. Other IMU positions on a helmet [22] or on the hip [23] or also approaches with multiple other sensors [24] have been investigated as well but positioning the IMU on the foot seems to be the method of choice in most of the published research on this topic in the last few years.

Published PDR accuracies are usually indicated in a percent value representing the mean deviation of the covered distance over time. The accuracies strongly depend on the used hardware and methodology. The published values range from under one percent [18] to a few percent [15], [16].

To cope with the PDR-inherent adding-up of errors over time, almost all of the existing approaches need to be combined with other localization technologies like GPS, RFID, map matching or others to achieve long-term accuracy. The prevalent technology for this is GPS and it is commonly assumed that a position update is performed whenever a reliable satellite signal is available, i.e., whenever the tracked pedestrian walks through a courtyard or close to a window [16], [17].

However, it is a fundamental problem of PDR that long term accuracy is difficult to achieve without the use of additional data input.

C. Hybrid WSN IMU Localization Systems

Combining the advantages of PDR with WSN localization techniques can allow to compensate for the shortcomings of the two technologies. A WSN localization approach can be used for long-term stability and the PDR can help to navigate through areas with poor coverage or to compensate for variances in the position estimation that result from RSS fluctuations. In [25] the authors combine wireless LAN fingerprinting localization with a foot mounted IMU and magnetometer and improve the localization accuracy by using extended Kalman filter (EKF) data fusion. Another approach is proposed in [26] where the authors improve the localization accuracy in a sensor network by fusing IMU data and experimentally demonstrate their setup.

However, assuming that every mobile node, i.e., every person that is to be localized is equipped with an IMU makes the system costly and complex.

III. Solution Concept and System Design

As of now, there is still a lack of systems in the field of ad-hoc localization for applications in which it is not possible to deploy an infrastructure before the localization is needed. This could for example be the case if firefighters enter a burning building and the officer in charge needs real time information about the approximate location of his men in the burning building [3]. Other examples could be found in mass casualty events where the logistical coordination of the operation depends on on-line information about the whereabouts of doctors and patients [4].

For such applications, it cannot be assumed that previous knowledge like a floor plan of the building or a map of the surroundings (map knowledge) is available. Moreover, a training phase is usually not possible.

A. Requirements Analysis

In these intended applications, the challenge is thus to provide a system that does not require a complex setup but can be installed in a self-organizing ad-hoc manner. The simpler the setup and the cheaper the required hardware, the better are the chances of success. A subset of the nodes can be assumed to be static, but the bigger part will be attached to moving persons and thus mobile. This makes a self-organizing architecture necessary that allows to cope with mobile nodes. This architecture has to be scalable in terms of communication bandwidth and computational limitations on each node for larger networks with $\geq$ 100 nodes (decentral position estimation). Concerning the required accuracy, it is normally sufficient for the intended applications to get approximate information on the position of a person (accuracy in the range of several meters). It is rarely needed to provide location information in the range of several centimeters as it is assumed for some RTLS (Section II-A). As measured RSS values have large deviations, the performed localization algorithm needs to be able to cope with these deviations and to be robust against single or multiple measurement outliers.

For the intended system the requirements can be summarized:

- Simplicity and self-organization: easy setup
- Scalability: networks with $\geq$ 100 nodes
- Accuracy: several meters
- Robustness: measurement outliers

To solve these requirements, a system concept is proposed where an ad-hoc infrastructure of anchor nodes is deployed and initial positions are estimated by means of PDR. These anchor nodes then broadcast their positions in regular intervals and mobile nodes (on-body nodes) calculate their approximate positions. The position estimation is done by evaluating RSS values of received broadcast messages via an EKF localization algorithm.

B. PDR Node Deployment

For the deployment of the nodes, a PDR concept is proposed to be integrated into the localization WSN. For the purpose of this paper and the described experiments in Section V, the influence of this deployment procedure on the resulting accuracy is investigated off-line. As the position errors that result from the PDR are non-deterministic, a deployment and position initialization of anchor nodes would result in the limitation to one specific problem instance and thus make a reproducible analysis difficult. To avoid this issue, the anchor nodes were brought out and RSS data were collected. The calculation of the influence of the error caused by PDR node deployment can then be evaluated off-line by simulating various PDR error settings for the experimentally collected RSS dataset.

In this simulation, the error introduced by the PDR node deployment is modeled based on an experimental study on the resulting accuracy and an analysis of other systems accuracies. With state of the art PDR systems and with comparable IMUs an error in the range of a few percent can be achieved [15], [16]. If more expensive IMU hardware is available, this figure can be brought down to under one percent [18]. These figures in combination with initial experiments on an XSens MTI-G IMU are used as input for the simulation.

C. Node Localization with Noisy Range Measurements

The power-loss of electromagnetic waves over the traveled distance in indoor environments can be approximated with the log-distance path-loss model:

$$PL = P + 10n \cdot log_{10}\left(\frac{d}{d_0}\right) + N_G \qquad (1)$$

This model is based on the Friis' transmission formula and permits to approximate the path-loss over the distance of electromagnetic waves in indoor environments. The path-loss PL $[dBm]$ for a given distance d is expressed as a function of the path-loss coefficient n, a reference measurement P of the received power at distance d_0, and a normally distributed noise term N_G. If d_0 is assumed to be 1 m, the parameters P and n can be experimentally determined. To invert this function is then a simple way to approximate a distance estimation between a sender and a receiver for a given RSS measurement on given hardware.

Other approaches for an on-line estimation of the path-loss coefficient without need for calibration have been proposed and will be a future research topic for the considered application [27].

For the estimation of the location of a sensor node based upon noisy range measurements an extended Kalman filter (EKF) is used. If a time discrete system model for each node is assumed, the state of this node (i.e. the position) at time step k is represented by $\vec{x}_k$ and the state transition ($\vec{x}_{k-1} \rightarrow \vec{x}_k$) can be modeled as follows:

$$\vec{x}_k = A_{k-1}\vec{x}_{k-1} + B_{k-1}\vec{u}_{k-1} + G_{k-1}\vec{\omega}_{k-1} \qquad (2)$$

A_{k-1} is the system matrix, $B_{k-1}\vec{u}_{k-1}$ represents the system input and $G_{k-1}\vec{\omega}_{k-1}$ is a noise term that is assumed to be normally distributed with mean zero. In this model, a measurement $\vec{y}_k$ at time step k is assumed to depend linearly on the (true) system state $\vec{x}_k$:

$$\vec{y}_k = H_k\vec{x}_k + \vec{\nu}_k \qquad (3)$$

For the considered system, the errors of the distance measurements are assumed to be normally distributed with mean zero and standard deviation $\vec{\nu}_k$ as no further knowledge is available.

However, the available measurements of the distance d to an anchor node at position $\vec{x}^L$ have a nonlinear relation with the position of the on-body node. A linear transformation matrix H_k cannot be found. For this purpose the EKF makes use of a linearization in the current operating point to calculate H_k: the measurement of the distance $h(\vec{x}) = \sqrt{\sum (x_i - x_i^L)^2}$ is linearized by calculating the Jacobian matrix for the current incremental values:

$$H_k = \frac{\partial h(\vec{x})}{\partial \vec{x}} \qquad (4)$$

The error caused by this linearization does not have a strong effect as long as the update rate of the system is sufficiently high.

For the intended person localization, a movement model is integrated by making use of the system equation. The prediction of the system state at time step k is $\vec{x}_k^-$. This prediction depends on the previous state estimation and the input $B_{k-1}\vec{u}_{k-1}$ from a movement model:

$$\vec{x}_k^- = A_{k-1}\vec{x}_{k-1} + B_{k-1}\vec{u}_{k-1} \qquad (5)$$

The covariance for this estimation at each time step k can then be estimated with:

$$C_k^- = A_{k-1}C_{k-1}A_{k-1}^T + Q_{k-1} \qquad (6)$$

based on the previous covariance C_{k-1} and the total noise input Q_{k-1} introduced by the movement model $B_{k-1}\vec{u}_{k-1}$ and the process noise $G_{k-1}\vec{\omega}_{k-1}$. If now a new measurement $\vec{y}_k$ is available, the resulting covariance for the next time step can be minimized by fusing the prediction for the next state $\vec{x}_k^-$ from the system model and the measurement into a new state estimate $\vec{x}_k$:

$$\vec{x}_k = \vec{x}_k^- + K(\vec{y}_k - h_k\vec{x}_k^-) \qquad (7)$$

The Kalman gain factor K in this equation is a function of the predicted measurement covariance R_k and the current position estimation covariance C_k^-.

$$K = C_k^- H_k^T (H_k C_k^- H_k^T + R_k)^{-1} \qquad (8)$$

The resulting new covariance C_k then becomes:

$$C_k = C_k^- - K H_k C_k^- \qquad (9)$$

The EKF provides a good estimate of the state of a system, if the errors are normally distributed with mean zero. The movement model has to be chosen with care to allow for a smoothening input into the filter.

For the implemented system, no further knowledge about the error distribution is assumed and the EKF is used with experimentally determined parameter settings.

IV. Implementation

For the practical evaluation of the proposed concept a system is implemented based on low-power sensor nodes and a ZigBee standard-conform network implementation.

A. Hardware

1) LocNode sensor node: The two implemented versions of the LocNode each consist of a Texas Instruments MSP430 MCU and a 2.4 *GHz* IEEE 802.15.4 compliant CC2520 radio chip. In the simple version of the LocNode a 3-axis MEMS acceleration sensor is included on the PCB (for movement detection) and the node is designed to fit into a robust 5.5 x 2 x 2.5 cm^3 casing, whereas the extended version allows for the connection of extension boards via two 20 pin connectors (Fig. 1).

Fig. 1. LocNode: extended version with attached GPS module and simple version in casing

The designed extension modules include an SD-card interface to be able to record RSS data during experiments for off-line processing and evaluation.

2) GPS module: To allow for an integration of GPS signals as proposed in Section III, a GPS module has been designed that connects to the extended version of the LocNode (Fig. 1, left).

3) Pedestrian dead reckoning unit: For the implementation of the PDR, a connection board has been designed that allows for the integration of an XSens MTI-G IMU with an extended LocNode. Experiments show that it is possible to reproduce state of the art PDR accuracies if the IMU is attached to the foot and the data processing is done off-line. Fig. 2 shows an example of a reconstructed trajectory of a pedestrian moving through the institute premises if zero-velocity updates are performed. An experimental evaluation revealed that accuracies in the range of 5 % of the walking distance can be achieved. These first results and the state of the art figures (Section III-B) are taken as an input into the deployment path simulation (Section V).

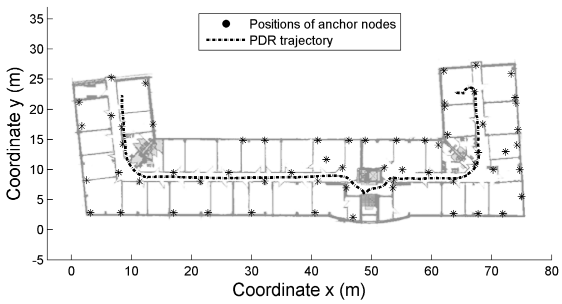

Fig. 2. PDR trajectory of test person (experimental data, off-line calculated) and positions of anchor nodes in our experiments

The improvement of the PDR accuracy and the implementation of an algorithm that can be computed on the used low-power MCU are topics of future research. Alternatively, an additional signal processing unit can be added to pre-process the IMU data.

B. Software

On the software side, a ZigBee application has been developed to allow for the formation and reliable operation of a larger scale sensor network without needing to develop on network layer level. The implemented modular application consists of a simple operating system as interface to the hardware, the communication layers of the ZigBee stack and a position calculation module on application level. The parameters of this module can be set via over-the-air download through the network. The stack is configured to automatically form a mesh network upon deployment and to allow for a multi-hop communication with up to 20 hops. All nodes incorporate the same application layer software and provide the functionalities as described in Section III.

At the current development state, ZigBee End Devices cannot be configured to receive and process broadcast messages which makes an implementation of an all-router network necessary.

V. Experimental Evaluation

To evaluate the presented concept, an experiment has been conducted with 65 LocNodes in the premises of the institute. On one floor of the office building, approximately 70 *m* long and 20 *m* wide, 60 anchor nodes were deployed as shown in Fig. 2.

A test person equipped with 5 on-body nodes (node 1: mounted on a rucksack, node 2: hanging on a lanyard in front of body, node 3: right trouser pocket, node 4: hanging on a lanyard behind body, node 5: left trouser pocket) moved through the building following predefined trajectories. Fig. 3 shows the trajectory of the third test run as an example. Each of the on-body nodes was equipped with an SD-card to be able to capture a total of 1,100,000 packets in 5 test runs through the building. The captured packets were correlated with the corresponding real position (ground truth) of the test person to be able to analyze the data off-line and evaluate different parameter settings on real data. The anchor nodes broadcast frequency was set to 4 *Hz* and at each discrete 0.25-second time step the received packets from the 16 strongest anchor nodes were recorded.

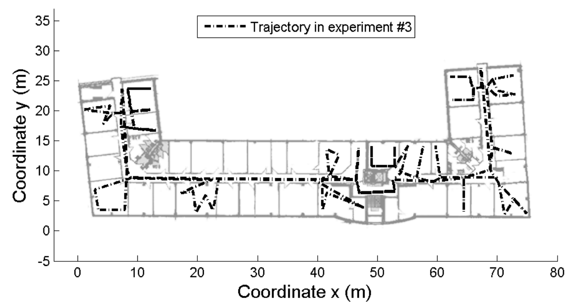

Fig. 3. Trajectory of test person in third run (ground truth)

All nodes were connected in a ZigBee network to allow for ad-hoc network formation and multi-hop communication. Each mobile node's calculated position estimation can then be communicated to a central data sink (network coordinator) in regular intervals. To be able to interpret the behavior of RSS values in indoor environments another data set was recorded in an outdoor experiment with 20 anchor nodes and 5 on-body nodes on a football field [28].

For the purpose of comprehensibility and reproducibility of the results, the anchor node positions and the test person's trajectory were exactly determined during the experiment. The analysis in the following chapter is calculated on the data collected during 5 experimental runs. The processing is done off-line to enable a simulation-based analysis of the influence of biased anchor node positions.

A. Data Analysis

Fig. 4 shows the RSS values of the recorded packets at increasing distances on a logarithmic scale (dBm). The darker, the more packets have been collected at a given distance for a respective RSS value. The lines represent the RSS means for the different nodes.

The recorded packets show the characteristic drop-off behavior over the distance. With regard to their RSS means, the different node positions on the body do not cause a big

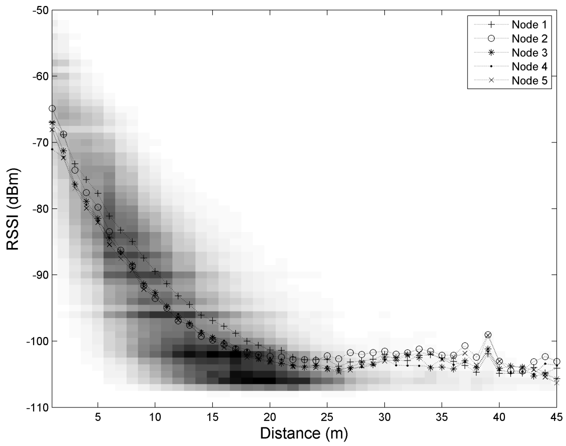

Fig. 4. Measured signal strength drop-off over distance

difference. As expected, the means of the recorded packets are higher for node number 1 which was carried on a rucksack and thus had a higher percentage of line of sight connection to the anchor nodes and less damping by the test persons body.

If the data set is inverted as perceived by a mobile node it can be seen that the standard deviation of the measurements increases with the distance (Fig. 5).

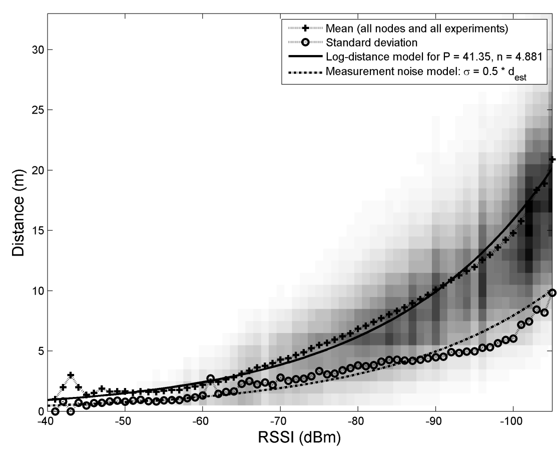

Fig. 5. Distribution of recorded RSS packets

The measured data were used to fit the parameters of the log-distance path-loss model (1) experimentally. As the measurement setup (Section V) in the institute premises did not allow to record distances higher than 65 *m*, measurements for higher distances are underrepresented in the collected data set (Fig. 4). Also, due to the fact that only packets from the 16 strongest anchor nodes were recorded, small RSS values are underrepresented.

The optimal least squares fit of the model for the recorded data is achieved for coefficients $n = 4.881$ and $P = 41.35$ and is used for the distance estimation in all presented experiments. The measured standard deviation is approximated with $\sigma = \frac{d}{2}$ and used as model for the measurement noise in the EKF (Fig. 5).

Fig. 6 gives an impression of the achievable accuracy of the distance estimations based on the recorded RSS values. Every data point represents the mean of five captured packets. Whenever the distance is bigger than around 30 *m*, the corresponding anchor node is usually not among the 16 strongest senders within range and thus no packets were recorded.

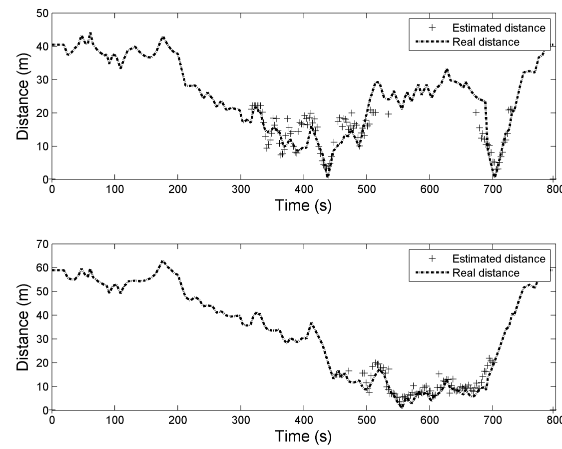

Fig. 6. Estimated and real distances for exemplary node

For the evaluation of the localization approach, range measurements with RSS values smaller than the receiver-sensitivity that was specified in the data sheet (-98 *dBm*) were not considered to prevent errors.

B. Localization Results

The presented EKF is now applied to estimate the position of the moving person in the sensor network. The metric for the evaluation and tuning of the algorithm is the performance in terms of mean and standard deviation of the difference between estimated and real position. The parameters of the EKF were set to provide optimal accuracy for all different node positions (node 1 - node 5, see Section V). The movement model was incorporated by linearly interpolating the last positions to estimate the next position for every 0.25-second time step. It is thus assumed that the tracked person moves in a certain direction for some time and does not move randomly. This movement model acts like a low-pass filter and compensates for the high variations in the distance measurements.

Fig. 7 shows an exemplary reconstructed trajectory for the data collected by the node hanging on a lanyard around the test persons neck (node 2) in the third experiment. The 5 experimental runs were different in terms of walking speeds and trajectories. With the outlined approach it is possible to achieve a mean localization accuracy on the order of $2.5 - 3.5$ *m* with a standard deviation on the order of 1.7 *m* for all nodes in all experiments if a single parameter setting

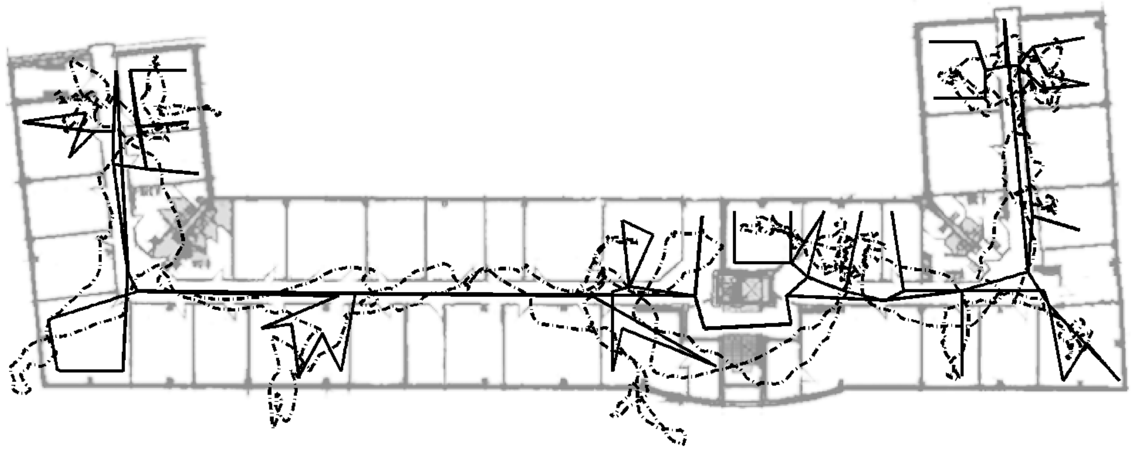

Fig. 7. Estimated (dotted line) and real trajectory (solid line) in experiment 5 for the RSS data of node 2 (mean deviation: 2.3 *m*)

is used (Tab. I). The accuracy of single nodes in some of the experiments can reach 2.3 *m*. If tuning the parameters to a single experiment, accuracies in the range of $1.3 - 1.4$ *m* are possible. For comparison, the presented trajectory in Fig. 7 has mean deviation of 2.3 *m* at a standard deviation of 1.7 *m*.

If considering all packets received at the same time by the five different on-body nodes, even better results can be achieved. From an implementation point of view this is however not desirable as it would require synchronization and additional communication overhead. It is intended to provide a simple PLS where it is sufficient to carry a single sensor node in a pocket or hanging from a lanyard around the test persons neck.

TABLE I
MEAN DEVIATIONS (IN M) FOR ALL NODES IN ALL EXPERIMENTS

exp. #	node 1	node 2	node 3	node 4	node 5
1	3.86	3.01	2.93	5.65	3.29
2	3.35	2.81	3.28	5.85	3.85
3	2.99	2.42	2.74	3.80	3.96
4	2.87	2.28	2.66	3.81	2.90
5	2.87	2.29	2.47	3.72	2.72

In the following, the position estimation is always carried out by considering the packets received by a single node. One fixed parameter setting has to lead to sufficiently accurate results for all different node positions, i.e., in one of the pockets or also on a band around a person's neck. This is because the intended application is an easy-to-use system where the user can carry the on-body node wherever he wants.

C. Biased Anchor Node Positions

It is now assumed that a subset of the anchor nodes has a good position estimation, for example due to a GPS signal at a window or due to a landmark based manual positioning. The remaining anchors get their initial position estimation upon deployment. The position accuracy of these nodes is thus corresponding to the accuracy of the PDR at the given point. To be able to quantify the impact of unknown anchor positions on the localization accuracy, the trajectory of the PDR node deployment was simulated for varying noise inputs in the PDR position estimation. Fig. 8 shows an exemplary simulated PDR trajectory and the resulting anchor node setting. In this example, 50 % of the anchor nodes are assumed to have a biased position estimation. The remaining nodes are accurately positioned due to an available GPS signal or a subsequent correction due to the placement at a landmark.

In the simulations it is assumed that the location error introduced by the PDR deployment consists of a random component that affects the estimated velocity and a random component that affects the accuracy at every turn. With this model it is possible to account for errors caused by the acceleration sensors as well as gyro sensors.

For a realistic evaluation of the system behavior it is assumed that the PDR deployment is carried out by a person entering the building. The deployment path is modeled starting at the entrance of the building and passing by every anchor node position one after the other. Own experiments as well as analysis of the state of the art indicate that the achievable total accuracy of a PDR unit is on the order of a few percent of the covered distance (Section III-B). A velocity error as well as an angle error were modeled, the parameters result in an error with mean of about 2 % of the covered distance.

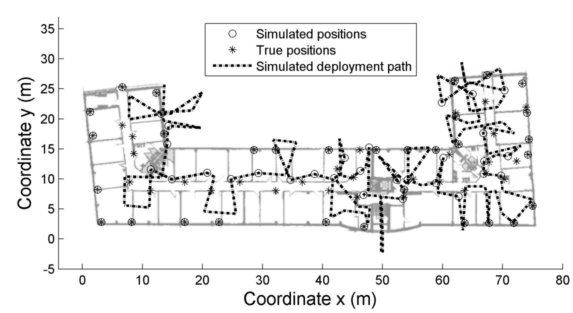

Fig. 8. Example for 50 % biased anchor node positions

To simulate an inaccurately positioned subset of anchor nodes allows to investigate the impact on the localization accuracy without needing to deploy the nodes multiple times. For the simulations the experimentally collected RSS data are used, and the source positions are adjusted subsequently. 100 different anchor node sets for stochastic PDR trajectories are used to achieve a significant quantity of setups to cope with random errors.

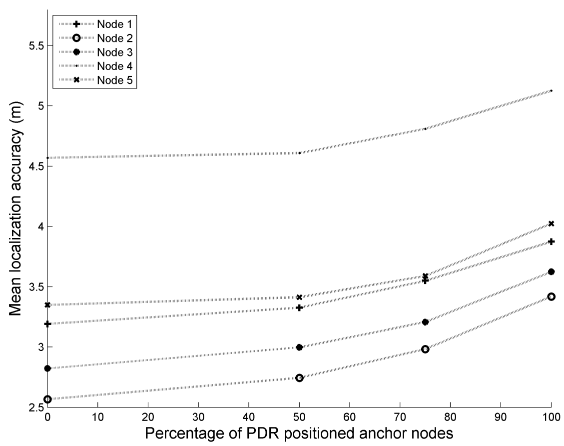

Fig. 9. Localization accuracies for decreasing percentage of accurately positioned anchor nodes

In Fig. 9 the presented absolute accuracies represent the mean of each node in all five experimental runs each for 100 different simulated anchor settings. The part of the anchor nodes that has a biased position estimation increases from 0 % to 100 %. If all anchor nodes are assumed to have accurately known positions the localization accuracy is on the order of 3 *m* depending on the positioning of the on-body nodes (node 1 - node 5). The poorer results for node 4 could be caused by its position on the test persons back and the resulting constant bias of the measurements into the reverse direction. If 50 % or 75 % of the nodes are positioned by a PDR and thus have a biased position estimation, the accuracy decreases (Fig. 9). However, the robustness of the outlined localization algorithm allows for a resulting accuracy under 5 *m* with a standard deviation under 2.5 *m* for all nodes in all setups even if all anchor nodes have only the PDR deployment position information available.

VI. Conclusion

In this paper a practical evaluation of an indoor WSN person localization system under real-world conditions is presented. Persons that carry on-body sensor nodes are to be localized within an ad-hoc WSN. It is evaluated what accuracies can be achieved under the condition that no map knowledge is available and the infrastructure for the system is set-up in an ad-hoc manner. Some anchor nodes in the network are GPS-equipped or manually configured with the correct position whereas others get their position estimations from a PDR device upon deployment. It is proposed to deploy the anchor nodes by means of a PDR and it is shown how resulting biased position estimates of subsets of anchor nodes influence the position estimation accuracy for mobile nodes. The experimental results demonstrate that RSS localization in indoor environments is possible and that accuracies on the order of a couple of meters can be achieved with reasonable numbers of nodes.

An initial experimental evaluation of the achievable accuracy with an X-Sens MTI-G IMU-based PDR is presented. The simulation setup is designed based upon this experimental evaluation and the analysis of state of the art approaches. For the estimation of the trajectory of a person in the network, an EKF is used to process RSS-based distance measurements. Results with a mean accuracy in the range of $2.5 - 3.5$ *m* are achieved if all anchor nodes have known positions. If up to 75 % of the anchor nodes have a biased position estimation the resulting accuracies decrease but remain in an acceptable range. Some aspects of the system need further work but the general idea works and the presented experiments show that ad-hoc localization can be achieved with a ZigBee WSN.

It can be concluded that the proposed system is principally suited to provide a cheap and scalable localization for large indoor environments where a number of persons needs to be tracked. The system design is scalable and large numbers of mobile nodes are not a problem. To the knowledge of the authors this approach to ad-hoc localization by PDR node deployment has not yet been experimentally investigated. Applications could possibly be found in the area of firefighters that enter a burning building or also in industrial maintenance applications where security regulations necessitate knowledge of the whereabouts of persons in the facility.

VII. Future Work

For the next future, it is planned to further investigate the behavior of the outlined localization algorithm for different scenarios. Then, the optimal parameter settings can be selected based upon a systematic evaluation of other state of the art localization approaches on the collected data. The goal is to identify the optimal localization approach for the given measurement setup and the given application.

Another opportunity is to investigate to what extend the errors introduced by the PDR deployment can be reduced after the network has been deployed. It is planned to update the anchor nodes' position estimations based on the packets they receive from their neighbors. To evaluate this, a simulation environment has been designed that allows to test approaches to achieve a refinement of the position estimation at runtime. These approaches will be the topic of a follow-up to this work.

On the side of the PDR unit development, it is at the moment investigated how to improve the state of the art pedestrian dead reckoning approaches and how to integrate the IMU-data with WSN hardware. A practical evaluation of the complete system including a real-world PDR node deployment will be possible as soon as the different parts have been integrated.

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References

[1] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, vol. 52, no. 12, pp. 2292–2330, 2008.

[2] M. Rudafshani and S. Datta, "Localization in wireless sensor networks," in *Proceedings of the 6th international conference on Information processing in sensor networks*. ACM, 2007, p. 60.

[3] C. Fischer and H. Gellersen, "Location and Navigation Support for Emergency Responders: A Survey," *IEEE Pervasive Computing*, vol. 9, no. 1, pp. 38–47, 2010.

[4] A. Chandra-Sekaran, A. Nwokafor, P. Johansson, K. Mueller-Glaser, and I. Krueger, "ZigBee Sensor Network for Patient Localization and Air Temperature Monitoring During Emergency Response to Crisis," in *The Second International Conference on Sensor Technologies and Applications*. IEEE, 2008, pp. 233–238.

[5] K. Lorincz, D. Malan, T. Fulford-Jones, A. Nawoj, A. Clavel, V. Shnayder, G. Mainland, M. Welsh, and S. Moulton, "Sensor networks for emergency response: Challenges and opportunities," *IEEE pervasive Computing*, vol. 3, no. 4, pp. 16–23, 2004.

[6] J. Zhang, P. Orlik, Z. Sahinoglu, A. Molisch, and P. Kinney, "UWB systems for wireless sensor networks," *Proceedings of the IEEE*, vol. 97, no. 2, pp. 313–331, 2009.

[7] Z. Xiao, Y. Hei, Q. Yu, and K. Yi, "A survey on impulse-radio UWB localization," *SCIENCE CHINA Information Sciences*, vol. 53, no. 7, pp. 1322–1335, 2010.

[8] I. Akyildiz, T. Melodia, and K. Chowdhury, "A survey on wireless multimedia sensor networks," *Computer Networks*, vol. 51, no. 4, pp. 921–960, 2007.

[9] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 37, no. 6, pp. 1067–1080, 2007.

[10] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *IEEE infocom*, vol. 2. Citeseer, 2000, pp. 775–784.

[11] H. Lee, M. Wicke, B. Kusy, and L. Guibas, "Localization of mobile users using trajectory matching," in *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*. ACM, 2008, pp. 123–128.

[12] D. Madigan, E. Einahrawy, R. Martin, W. Ju, P. Krishnan, and A. Krishnakumar, "Bayesian indoor positioning systems," in *Proceedings IEEE INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies*, 2005, pp. 1217–1227.

[13] K. Whitehouse, C. Karlof, and D. Culler, "A practical evaluation of radio signal strength for ranging-based localization," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 11, no. 1, p. 52, 2007.

[14] C. Morelli, M. Nicoli, V. Rampa, U. Spagnolini, C. Alippi, D. e Informazione, and I. Milano, "Particle filters for RSS-based localization in wireless sensor networks: An experimental study," in *Proc. IEEE Int. Conf. Acoust, Speech, Signal Process.(ICASSP 2006*, vol. 4, 2007, pp. 957–960.

[15] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Computer Graphics and Applications*, pp. 38–46, 2005.

[16] S. Godha and G. Lachapelle, "Foot mounted inertial system for pedestrian navigation," *Measurement Science and Technology*, vol. 19, p. 075202, 2008.

[17] R. Feliz, E. Zalama, and J. García-Bermejo, "Pedestrian tracking using inertial sensors," *Journal of Physical Agents*, vol. 3, no. 1, pp. 35–42, 2009.

[18] L. Ojeda and J. Borenstein, "Non-GPS navigation with the personal dead-reckoning system," in *Proceedings of the SPIE Defense and Security Conference, Unmanned Systems Technology IX*. Citeseer, 2007.

[19] J. Bancroft, G. Lachapelle, M. Cannon, and M. Petovello, "Twin IMU-HSGPS integration for pedestrian navigation," in *Proc. of ION GNSS*, 2008.

[20] J. Borenstein, L. Ojeda, and S. Kwanmuang, "Heuristic reduction of gyro drift in IMU-based personnel tracking systems," in *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, vol. 7306, 2009, p. 26.

[21] A. Jimenez, F. Seco, J. Prieto, and J. Guevara, "Indoor Pedestrian Navigation using an INS/EKF framework for Yaw Drift Reduction and a Foot-mounted IMU," *Proceedings of the 7th Workshop on Positioning, Navigation and Communication, March 11-12, 2010, Dresden, Germany*, 2010.

[22] S. Beauregard, "A helmet-mounted pedestrian dead reckoning system," in *Proceedings of the 3rd International Forum on Applied Wearable Computing (IFAWC 2006)*. Citeseer, 2006, pp. 15–16.

[23] M. Kourogi, N. Sakata, T. Okuma, and T. Kurata, "Indoor/outdoor pedestrian navigation with an embedded gps/rfid/self-contained sensor system," *Advances in Artificial Reality and Tele-Existence*, pp. 1310–1321, 2006.

[24] V. Renaudin, O. Yalak, and P. Tomé, "Hybridization of MEMS and assisted GPS for pedestrian navigation," *Inside GNSS*, vol. 2, no. 1, pp. 34–42, 2007.

[25] K. Frank, B. Krach, N. Catterall, and P. Robertson, "Development and Evaluation of a Combined WLAN Inertial Indoor Pedestrian Positioning System," *Working Paper. 2009. Print*, 2009.

[26] L. Klingbeil and T. Wark, "A wireless sensor network for real-time indoor localisation and motion monitoring," in *Proceedings of the 7th international conference on Information processing in sensor networks*. IEEE Computer Society, 2008, pp. 39–50.

[27] G. Mao, B. Anderson, and B. Fidan, "Path loss exponent estimation for wireless sensor network localization," *Computer Networks*, vol. 51, no. 10, pp. 2467–2483, 2007.

[28] J. Schmid, T. Anselm, M. Mairbäurl, W. Stork, and K. Müller-Glaser, "An approach to robust sensor network localization ," *Proceedings of the Seventh International Conference on Networked Sensing Systems*, pp. 340–341, 2010.