A SELF-CALIBRATING BIDIRECTIONAL INDOOR LOCALIZATION SYSTEM

Nizam Kuxdorf-Alkirata, Thomas Werthwein, Anna Heinemann and Dieter Brückmann

School of Electrical, Information and Media Engineering
University of Wuppertal, Rainer-Gruenter-Str. 21, 42117, Wuppertal, Germany
{alkirata, werthwein, heinemann, brueckm}@uni-wuppertal.de

ABSTRACT

In this contribution an improved approach for indoor localization based on low cost Bluetooth Low Energy (BLE) systems is proposed. The measured Received Signal Strength Indicator (RSSI) values, which are available in Bluetooth systems anyway, are used for localization. It is well-known that localization based on RSSI measurements can only be achieved with a limited accuracy when applying these values directly to respective path loss models. Therefore additional signal processing is performed on the RSSI values and an auto-calibration approach is proposed, which takes inconsistencies with respect to environmental textures into account. The respective model parameters can be thus matched and updated in regular intervals. Further improvements are obtained by performing distance estimation in both directions, namely from transmitter to receiver and vice versa. Furthermore a sophisticated post processing of the RSSI values is performed. Compared to established RSSI-based localization methods based on low-power, low-cost systems, the localization accuracy has been significantly improved by applying the proposed methods. This is verified by measurements using an experimental setup.

Index Terms— Indoor localization, BLE, RSSI

1. INTRODUCTION AND RELATED WORK

A large number of different Indoor localization methods are described in the literature and some of them are already implemented in commercial products. None of them however fulfills all requirements with respect to low cost, low power, fast tracking, reliability and sufficient accuracy at the same time. Most of the methods proposed can be either classified as a range-free or a range-based localization approach. Whereas the former is associated with significant inaccuracies with respect to location estimation, the latter can provide a higher precision. Range-based localization in wireless sensor networks is based on the idea of receiving and processing signals from fixed nodes and using the respective measurement values for estimation of the mobile node location [1, 2]. A very high accuracy can be achieved by approaches based on Time Of Arrival (TOA) and Time Difference Of Arrival (TDOA) techniques. For these methods however a strict time synchronization of the entire wireless network is required, which makes the implementation costly and thus not suitable for deployment in systems we are looking at [3]. When using the Angle of Arrival (AOA) method additional hardware is required in the receiver in order to calculate the relative orientation based on the measured arrival direction [4]. Thus implementation costs and power consumption of the receiver are increased.

A very simple method for localization is based on the idea of applying the measured RSSI values, which are available in the receiver anyway, also for localization. Since no additional hardware and no time synchronization is required in this case, this approach is simple, fast and very cost effective. RSSI based localization methods can be subdivided into algorithms based on fingerprinting and algorithms based on a model of the signal propagation path. Both methods are used in localization based e.g. on Wi-Fi systems [5].

Fingerprinting is known as an accurate but time consuming method for localization. Algorithms based on this method are carried out in two phases commonly known as the offline and the online phase. The location subject to analysis is divided into rectangular grids. Reference RSSI values corresponding to these grids are gathered during the offline phase, whereas the location estimation is carried out in the online phase. In [6] an indoor positioning approach for a Bluetooth network using fingerprinting is presented. Inconsistencies in the measured RSSI values are removed by an additional gradient filter. According to the authors, the maximum deviation of the estimated from the exact position was $2.67\mathrm{m}$ using this method. This seems to be a rather modest result for the time consuming and complex fingerprinting technique. In [7] a BLE indoor positioning method is proposed which uses Gaussian filtering for processing the RSSI values and least squares based piecewise fitting for online training. Applying this method the maximum deviation of the estimated position from the exact one was smaller than $1.5\mathrm{m}$ in 80% of the cases. In [8] a comparison of indoor localization based on Wi-Fi and Bluetooth Low Energy systems is presented. Again fingerprinting was applied as the technique used for localization. Based on the Wi-Fi system in 95% of the cases the deviation of the estimated from the exact position was smaller than

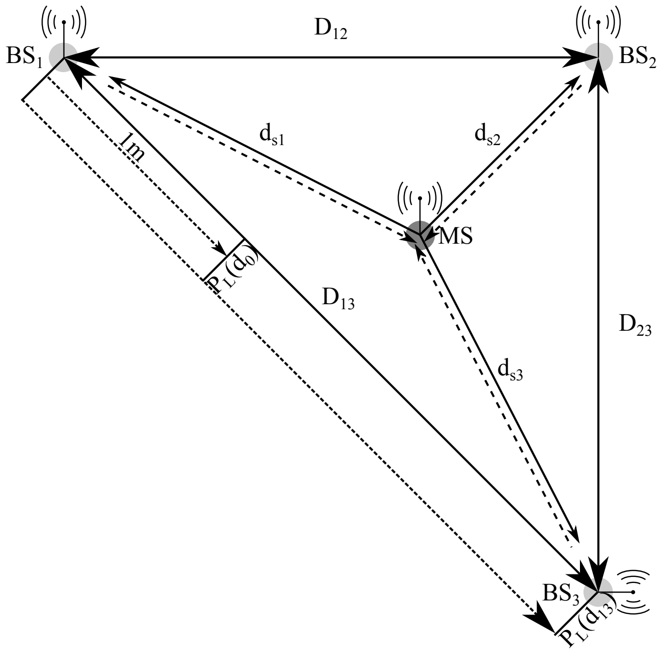

Fig. 1. Measurement configuration with base stations BS_1 to BS_3 and mobile sensor MS to be localized. D_{12}, D_{13} and D_{23} are the distances between the base stations, and d_{s1}, d_{s2} and d_{s3} are the distances between the MS and the base stations.

$8.5\mathrm{m}$. When using the BLE system the deviation was reduced to less than $2.6\mathrm{m}$ in 95% of the cases. The improved accuracy of the BLE based localization can be explained by the greater density of beacons (19 beacons) and the faster beaconing rate. Further fingerprinting techniques are presented in [9].

The iBeacon protocol developed by Apple Inc. can be also used for indoor localization as has been shown e.g. in [10]. This technology was already announced in 2013 on the World Wide Developers Conference (WWDC) and the protocol also works with Bluetooth Low Energy. This approach is based on a map containing the locations subject to analysis and the positions of the iBeacon senders. This map is created in advance. It was shown that the achieved precision in a clear line-of-sight environment is in the range of $1\mathrm{m}$, which drops heavily to $5\mathrm{m}$ in the presence of obstacles. In the following it will be shown that the accuracy of a localization algorithm can be considerably improved by applying novel methods proposed in this paper. The deviations from the exact positions had been lowered to less than $0.3\mathrm{m}$ in most of the cases.

2. SYSTEM CONFIGURATION AND INITIALIZATION PHASE

The system configuration used for localization of a mobile sensor MS is shown in Fig. 1. In order to determine its position, a MS must receive the transmitted signals from three fixed Bluetooth stations, which are designated as BS_1 to BS_3 in Fig. 1. The distances between the mobile sensor and the fixed stations BS_i can be estimated from the RSSI values by using the path loss model described e.g. in [11]. For indoor localization following relationship between distance d and path loss P_L in dB turns out to be appropriate:

$$P_\mathrm{L}(d) = P_\mathrm{L}(d_0) + 10\gamma \cdot \log_{10}\left(\frac{d}{d_0}\right) \qquad (1)$$

Where d_0 is the reference distance, $P_\mathrm{L}(d_0)$ is the respective path loss in dB and γ is the path loss exponent. There have been many attempts by researchers to enhance this model by adding further parameters obtained from measured data. Examples can be found in [12, 13, 14]. The results presented in this paper show however that distance estimation based on (1) is sufficient when proper adjustment of the parameters $P_\mathrm{L}(d_0)$ and γ is performed.

In the initialization phase, the first step of calibration, values $P_\mathrm{L}(d_0)$ and γ are determined for the actual system environment. The reference distance d_0 is set to 1m. Two sets of values are determined in this phase. Set 1 represents the reference path loss or reference RSSI values at a one meter obstacle free distance from the mobile sensor to each of the three fixed stations in the direction of the other two. The second set of parameters consists of the six RSSI values $RSSI_{i,j}$ with $i = 1, 2, 3$, $j = 1, 2, 3$ and $i \neq j$. $RSSI_{i,j}$ is the value measured at base station j when base station i transmits a beacon. Based on these two sets of values, the path loss exponent γ can be determined for each base station. Solving (1) for γ and with reference distance $d_0 = 1\mathrm{m}$, following relationship is obtained:

$$\gamma = \frac{P_\mathrm{L}(d) - P_\mathrm{L}(d_0)}{10 \cdot \log_{10}(d/d_0)} \qquad (2)$$

Note that for each path between two base stations γ is calculated twice by performing measurements in both directions. Thus six different values for γ are obtained for the configuration in Fig. 1. For a better understanding of the presented approach, we will consider in the following the determination of the path loss exponent $\gamma_{1,3}$ for a transmission from BS_1 to BS_3. With $D_{1,3}$ the distance between the two base stations and $RSSI_{1,3}$ the measured RSSI value at BS_3, following relationship is obtained:

$$\gamma_{1,3} = \frac{RSSI_{1,3} - P_\mathrm{L}(d_0)}{10 \cdot \log_{10}(D_{1,3}/d_0)} \qquad (3)$$

The path loss exponent $\gamma_{3,1}$ for the opposite direction can be determined respectively. The distance between the mobile sensor and the fixed station will be then calculated twice using these path loss values $\gamma_{1,3}$ and $\gamma_{3,1}$.

3. LOCALIZATION ALGORITHM

In Fig. 1 the configuration with three base stations used for position estimation is shown. The moving target to be localized is represented by the mobile sensor MS. The steps involved in the localization process are explained in this section. Since RSSI measurements are subject to noise, RF and environmental textures, they are preprocessed before they are used for distance calculation. This preprocessing is carried out by optimized digital filtering and is performed in two steps, which are called RSSI averaging and RSSI smoothing in the following.

3.1. RSSI Averaging

During the averaging operation the received RSSI values are weighted based on their time of arrival. More weight is placed on newer received values compared to older ones. RSSI values which are too old are discarded. Assuming that the newest RSSI value is received at time instant t_k, the respective RSSI average value $\overline{R_{si}(t_k)}$ obtained by time-based weighting of the last n RSSI values is given by:

$$\overline{R_{si}(t_k)} = \sum_{l=0}^{n-1} w_l \cdot R_{si}(t_{k-l}) \tag{4}$$

$R_{si}(t_{k-l})$ is the RSSI value received at time instant t_{k-l}, measured between a base station i and the mobile sensor MS, and w_l is the corresponding weight which is calculated by:

$$w_l = \frac{\mathrm{e}^{-(t_k - t_{k-l})/T_{\mathrm{ref}}}}{\mu} \tag{5}$$

The value μ is a factor used for normalization and $\Delta t = t_k - t_{k-l}$ is the elapsed time between the newest value at time instant t_k and the value received at time instant t_{k-l}. The reference time T_{ref} is chosen to be 1s.

3.2. RSSI Smoothing

The smoothing of RSSI values is also time-based and is performed after averaging. The respective values are determined by:

$$\begin{aligned}\widetilde{R_{si}(t_k)} = &\left[1 - (\alpha \cdot (1-\alpha)^{\Delta t/T_{\mathrm{ref}}}\right] \cdot \overline{R_{si}}(t_k) \\ &+\alpha \cdot (1-\alpha)^{\Delta t/T_{\mathrm{ref}}} \cdot \overline{R_{si}}(t_{k-1})\end{aligned} \tag{6}$$

Where Δt is the elapsed time between two measurements, namely at time instant t_k and t_{k-1} and α = 0.5. Due to these averaging and smoothing operations the impact of outliers on the localization process is very low.

3.3. Auto-Calibration

In this subsection a novel method for calibration is proposed which results in a considerably improved localization accuracy. The method is based on the idea of adaptively adjusting the path loss models for the different transmission paths. Thus changes in the environmental textures can be taken into account very rapidly. Whereas the reference path loss values $P_{\mathrm{L}}(d_0)$ measured at a $1\mathrm{m}$ distance from the base stations are assumed to be constant, the RSSI values $RSSI_{i,j}$ measured between the base stations can change due to room temperature variations, frequency interferences, humidity etc. According to (3) this results in a different path loss exponent $\gamma_{1,3}$ and the path loss model has to be adjusted. Thus it is proposed to perform calibrating of the path loss in regular time intervals in order to improve the accuracy obtained for distance estimation of the target. It has been confirmed by experimental results that the localization accuracy can be considerably improved by applying this method. These experimental results will be described in section 4.

Since each BS is equipped with a receiver, changes in the field strength values $RSSI_{i,j}$ can also be detected during the localization procedure. Packets arriving at each BS_i from the other two can be identified by the respective MAC address contained in the received signals. The corresponding $RSSI_{i,j}$ values will undergo time-weighted averaging and smoothing and then are used for the calculation of the new path loss exponents of the corresponding path. This process of repeated calculation of the path loss exponent for the paths between the fixed base stations is applied simultaneously to the localization procedure and is referred to by auto-calibration.

3.4. Bidirectional Distance Calculation

In this subsection another new method will be described, which was developed for increasing localization accuracy. Existing approaches of RSSI based distance estimation normally use signal transmissions only in one direction. Either the fixed base stations transmit a beacon, which is received by the target MS or conversely, the MS is used as the transmitter and the fixed BS_s are the receivers. In order to improve the performance of the localization procedure this method is extended by performing RSSI measurements in both transmission directions and using both values for localization. Thus the respective distance between MS and BS is estimated two times based on different measurements and this information can be used for improving localization accuracy. Data packets containing the RSSI value of the MS, the target subject to localization, are identified at each BS based on their mac address. Then an optimized filtering of these RSSI values is performed and the distance is estimated. For a trilateration-based localization, the position of three reference points and the distances of the subject to be localized to these points are needed. By applying the bidirectional distance estimation 6 values for the distances are obtained in each iteration step of the algorithm. Thus 2^3 different position estimations can be determined by the algorithm. After discarding outliers the final position is estimated then by averaging the remaining values. The distance d_{si} between each MS, BS pair can be estimated from the respective measured field strength value $P_{\mathrm{L}}(d_{si})$ by:

$$d_{si}/\mathrm{m} = 10^{\frac{P_{\mathrm{L}}(d_{si}) - P_{\mathrm{L}}(d_0)}{10\gamma}} \tag{7}$$

This relationship is obtained by solving (1) for d and with reference distance $d_0 = 1\mathrm{m}$. The distances d_{s1}, d_{s2} and d_{s3} in Fig. 1 are estimated for both directions using this relationship.

3.5. Bidirectional Weighting Procedure

As already mentioned in section 2, distance calculation between MS and each base station BS_i is performed twice based on two different path loss exponents available for the link to each base station. Thus two different values $d_{si,1/2}$ for the estimated distance are obtained, which are combined by a weighted averaging operation to the final value d_{si}. d_{si} is then used for localization. The respective weighting operation can be described by following relationship:

$$\overline{d_{si}} = \frac{w_1 \cdot d_{si,1} + w_2 \cdot d_{si,2}}{w_1 + w_2} \tag{8}$$

The weights $w_{1/2}$ are determined by taking the estimated distances of the MS to the respective other two base stations into account. These are e.g. BS_2 and BS_3 if the link between MS and BS_1 is considered and path loss exponents $\gamma_{1,2}$ and $\gamma_{1,3}$ are used for distance estimation. It is assumed that distance estimations based on larger RSSI values are more reliable. Thus more weight is assigned to an estimated distance based on larger RSSI values respectively.

4. EXPERIMENTAL RESULTS

The performance of the proposed algorithm was evaluated by performing field trials with an experimental setup. The measurements had been carried out in a room of size $5.6\mathrm{m} \times 6.4\mathrm{m}$. The respective experimental system configuration is shown in Fig. 2. The three base stations have been deployed at locations with known coordinates. The exact position of the mobile sensor in Fig. 2 is given by the coordinates $(1.5, 1.4, 1.0)$. In a first step this position was estimated without applying the proposed methods. Distance estimation was carried out based on the path loss exponents that had been determined during the initialization phase. Position calculation was repeated at different times of the day so that not only static, but also dynamic characteristics of the environment are taken into account. The estimated positions were randomly scattered around the actual position as is shown by the black triangles in Fig. 2. It turned out that more than 90% of the calculated positions were closer than $40\mathrm{cm}$ to the real position. In a second step the experiment was repeated under the same conditions but position estimation was performed by also applying auto-calibration and bidirectional distance measurement. Thus localization accuracy could be considerably improved

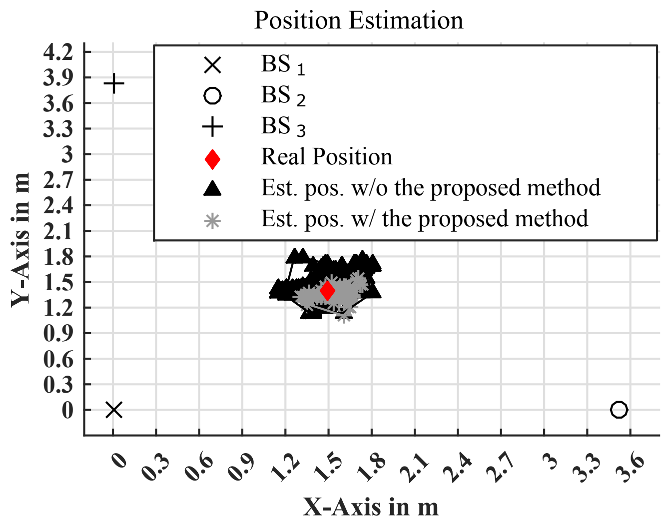

Fig. 2. Improvement of localization accuracy by applying the proposed method of auto-calibration and bidirectional distance measurement.

as shown by the gray stars in Fig. 2. In 95% of the cases the maximum deviation was now smaller than $24\mathrm{cm}$. Position estimation for other locations of the MS in the test area confirmed the results. Only locations on the direct path between the BS_s turned out to be more critical. For these cases auto-calibration is disturbed by the MS so that the estimated path loss exponents are not correct and the deviation of the estimated positions is larger. Note that the real-time capability of the presented indoor positioning system is still maintained after applying the methods.

5. CONCLUSION

In this contribution an enhanced positioning algorithm is proposed based on RSSI measurements. The reliability of a self-calibrating bidirectional indoor localization system based on Bluetooth Low Energy (BLE) is investigated. Since fluctuations with respect to RSSI measurements have a significant impact on the correspondent path loss exponent and hence on distance estimation, we proposed an auto-calibration method which calculates the path loss exponent repeatedly and simultaneously to the localization process and thus takes into account changes in the environmental texture. By applying bidirectional distance estimation 2^3 different constellations are available for position calculation by trilateration. Localization accuracy in a typical BLE environment was improved based on our proposed methods and the experimental results confirmed the expected performance of the algorithm.

In future work and in order to further improve the positioning accuracy, the localization process will be supported through inertial sensors, which provide information about acceleration, location and magnetic field.

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