Analysis of RSS-based Location Estimation Techniques in Fading Environments

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***Abstract*—Distance estimation techniques based on RSS (received signal strength) measurements put low demand on the hardware and software complexity of the infrastructure components. On top of several distance calculations a location estimation algorithm is used to compute the position of an unknown node. The algorithms differ in their complexity, expressed by the need of computation time, and in the achievable accuracy of the position estimation. Experimental results in a real life indoor scenario with 2.4 GHz RF transceivers and multipath fading channels show that an approximative location estimation algorithm like an extended centroid localization method can reach a higher accuracy than an exact mathematic least squares approach, although the resource-aware centroid localization method has a significant lower complexity than the least squares approach.**

***Index Terms*—Indoor Localization, Signal Fading, 2.4 GHz ISM Radio, Received Signal Strength Readings, Centroid Location Estimation, Linear Least Squared Error Estimator.**

I. Introduction

Indoor localization systems are ubiquitous and can be found in nearly every area of modern life. They can be used for the navigation of pedestrians in indoor areas or urban canyons where the availability of the global positioning system (GPS) is limited. Another possible application is described in [1] where we proposed a local positioning system based on received signal strength (RSS) measurements of radio (RF) signals for the monitoring of maintenance staff in the underground longwall coal mining.

A classification of localization techniques is given in Fig. 1. The systems can be divided according to their physical measurement domain. The use of directional sensors like infrared (IR), ultrasound, optical and magnetic systems is limited to line-of sight (LOS) scenarios. Typical indoor environments are often obstructed with many non-line-of sight (NLOS) conditions and thus make it challenging to get a reliable position information. An inertial navigation system (INS) or an RF localization system can be used for heavy obstructed NLOS scenarios, while the RF ranging sensors are more error-prone due to the multipath fading effects [2]. Nevertheless, RSS-based distance estimation techniques put low demand on the hardware and software complexity of the infrastructure components and thus, are widely distributed. E.g. the Horus system [3] or the commercial Ekahau location engine use RSS measurements.

Beside RSS measurements also time of flight measurements (TOA, TDOA) or direction of arrival measurements (AOA) are

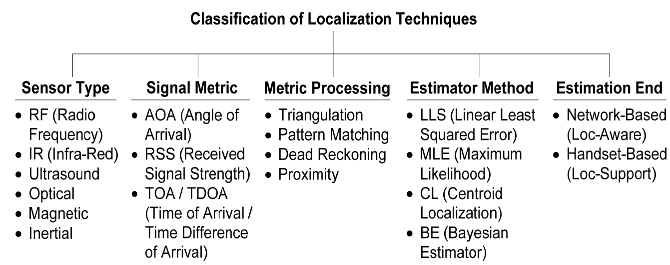

Fig. 1. Taxonomy of localization techniques according to the used sensor, the signal processing and the location estimator. Source: Own elaboration

used as an RF signal metric to calculate the distance between the transmitter and the receiver. The disadvantage is the need of additional hardware and software components. E.g. precise timers are required for the synchronization of TOA and TDOA techniques.

A good overview with a comparison of the accuracy and the coverage of the different indoor positioning techniques is given in [4]. A more general taxonomy of localization systems can be found in [5]. In [1] we investigated the influence of a diversity platform and an inertial navigation aid on the accuracy of an RSS-based localization system. The issue of our present work focuses on fault-tolerant location estimation algorithms for RSS-based systems which enable an adequate accuracy at minimum costs.

In section II, the propagation of RF signals in indoor scenarios is explained and a path loss model is derived. The results from a path loss measurement in a real life scenario are presented and compared to the theoretical model. In section III, different location estimation techniques are discussed with a focus on range-based centroid localization methods. In section IV, experimental results of a dynamic tracking measurement on a motion test track for different location estimation techniques are given. In the last section V, the results are discussed and investigated in terms of an outlook for further system developments.

II. Indoor RF Signal Propagation

A. Path Loss Model

Without any disturbances (free space propagation) the distance-depending path loss shows a logarithmic dropping of power with a linear increasing distance according to the Log-distance path loss model. With (1) the average path loss $\overline{PL}(d)$ (in dBm) over a distance d is given by the reference path loss

$PL(d_0)$ over a reference distance d_0 and the environment-specific propagation coefficient n.

$$\overline{PL}(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right). \tag{1}$$

The value of $PL(d_0)$ is influenced by the effective radiated power (ERP) of the RF transmitter and the gain of the transmitting and receiving antenna. For a 802.15.4 compliant $2.4\,\mathrm{GHz}$ ISM transceiver with an output power of $+10\,\mathrm{dBm}$ we have investigated a $PL(d_0)$ of $-67\,\mathrm{dBm}$ at $d_0 = 1\,\mathrm{m}$.

The value of n is influenced by the specific environmental propagation conditions and the used frequency. In [6] values for n between 1.8 and 3.2 are given for obstructed indoor environments and frequencies between $900\,\mathrm{MHz}$ and $4.0\,\mathrm{GHz}$.

In Fig. 2 the average path loss $\overline{PL}(d)$ for these two values of n are shown on the left as a function of the distance between transmitter (TX) and receiver (RX). The corresponding probability density functions (PDFs) for the distribution of $PL(d)$ at the receiver ($PL(d_{RX})$ – i.e. RSS value) are shown on the right.

In obstructed indoor environments not only NLOS conditions but multipath signal fading affects the RF signal propagation. The fading follows a Rayleigh distribution. The PDF of the distribution is defined as follows:

$$f(x,\theta) = \begin{cases} \frac{x e^{-\frac{x^2}{2\theta^2}}}{\theta^2} & , x \geq 0 \\ 0 & , x < 0 \end{cases} , \tag{2}$$

where the maximum likelihood estimator of θ is defined as

$$\theta = \sqrt{\frac{1}{2N}\sum_{i=0}^{N} x_i^2}. \tag{3}$$

The expectation value $E(X_r)$ of the Rayleigh distribution is defined as

$$E(X_r) = \theta\sqrt{\frac{\pi}{2}}. \tag{4}$$

The distance dependent path loss from (1) is an average value and therefore not suitable to describe a real channel. For obstructed indoor environments a zero-mean Gaussian random variable X_σ with standard deviation σ is added to the average path loss:

$$PL(d) = PL(d_0) + 10n \log\left(\frac{d}{d_0}\right) + X_\sigma. \tag{5}$$

X_σ can be described with the standard deviation σ of the Rayleigh distribution which is defined as follows:

$$\sigma = \sqrt{\frac{4-\pi}{2}\theta^2}. \tag{6}$$

With (1) and a reference path loss $PL(d_0)$ at a distance $d_0 = 1\,\mathrm{m}$ the distance between transmitter and receiver can be calculated with

$$d = 10^{\left(\frac{PL(d_{RX}) - PL(d_0)}{10n}\right)}, \tag{7}$$

where $PL(d_{RX})$ is the path loss measured at the receiver.

B. Real Life Path Loss Measurement

To investigate the path loss in indoor environments we have carried out a measurement on a motion test track in an industrial like test hall (cf. Fig. 6). The RSS over a distance of $11\,\mathrm{m}$ is shown in Fig. 3 where the small-scale fading due to the multipath propagation is pointed out.

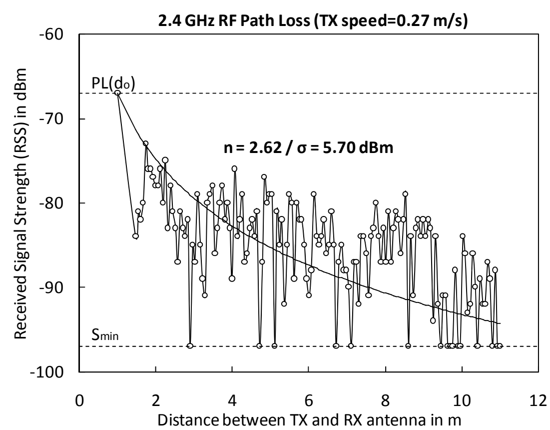

Fig. 3. Path loss measurement for $2.4\,\mathrm{GHz}$ over a distance of $11\,\mathrm{m}$ (150 RSS samples, TX speed = $0.27\,\mathrm{m/s}$, $5\,\mathrm{Hz}$ update rate). Source: Own calculation

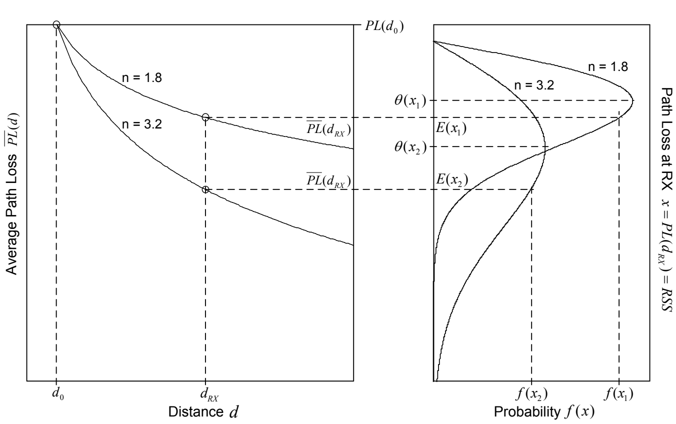

Fig. 2. Log-normal path loss model (left) and PDFs (right) for two different fading channel estimations ($n = 1.8$ and $n = 3.2$). Source: Own elaboration

The destructive interferences of different multipath signals lead to abrupt signal dropouts where the signal sometimes even falls below the receiver's sensitivity level S_{min} and the transmitted information gets lost. Even if the information arrive the receiver, the measured RSS can not be assigned to a single distance. The error-prone behavior of RSS-based distance estimations should be taken into account at the algorithmic level of the location estimation.

III. Location Estimation Techniques

A classification of localization techniques according to the metric processing and the estimation method is given in Fig. 1. For a dynamic environment with moving obstacles the scene analysis (pattern matching) technique is challenging because it is based on a static a priori knowledge of the environment. A metric processing with triangulation of a set of distance estimations or a proximity method are more useful for an obstructed indoor environment with changing propagation conditions. In the following two specific location estimation algorithms for range-based systems are presented and compared.

A. Linear Least Squared Error

The method of linear least squared (LLS) errors is a mathematically exact approach for the triangulation technique using a measurement set of distances or angles between a mobile BN and a number of fixed RNs. For a two-dimensional localization the distance to three RNs is required to compute the position of the BN. With more than three RNs the resulting linear system is overdetermined. In Fig. 4 a configuration of four RNs is shown. The circles, representing the estimated distances, are not crossing each other in one single point. Thus, there exist no exact solution for the system.

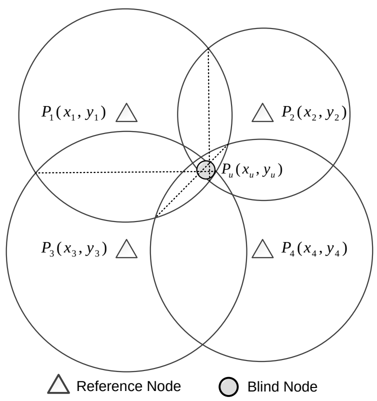

Fig. 4. Linear least squared error method for a two-dimensional localization using a set of four reference nodes (RN1 is used for the linearization). Source: Own elaboration

The LLS approach minimizes the sum of squared errors of the erroneous distance estimations $\tilde{d}_j(j = 2, ..., N_{RN})$ to N RNs to solve the following system of equations:

$$(x_u - x_j)^2 + (y_u - y_j)^2 = \tilde{d}_j^{\,2}. \tag{8}$$

For the solution first a linearization of (8) is done by subtracting the location of the first RN from all other equations [7]. The new systems of equations has the matrix form $\mathbf{Ax} = \mathbf{b}$ with

$$\mathbf{A} = \begin{pmatrix} 2x_1 - 2x_2 & 2y_1 - 2y_2 \\ 2x_1 - 2x_3 & 2y_1 - 2y_3 \\ ... & ... \\ 2x_1 - 2x_n & 2y_1 - 2y_n \end{pmatrix}, \tag{9}$$

$$\mathbf{b} = \begin{pmatrix} \tilde{d}_2^{\,2} - \tilde{d}_1^{\,2} + {x_1}^2 - {x_2}^2 + {y_1}^2 - {y_2}^2 \\ \tilde{d}_3^{\,2} - \tilde{d}_1^{\,2} + {x_1}^2 - {x_3}^2 + {y_1}^2 - {y_3}^2 \\ ... \\ \tilde{d}_n^{\,2} - \tilde{d}_1^{\,2} + {x_1}^2 - {x_n}^2 + {y_1}^2 - {y_n}^2 \end{pmatrix}, \tag{10}$$

$$\mathbf{x} = \begin{pmatrix} x_u \\ y_u \end{pmatrix}. \tag{11}$$

The estimated position of the BN can be calculated with the LLS method, solving the following equation:

$$\begin{pmatrix} \hat{x}_u \\ \hat{y}_u \end{pmatrix} = (\mathbf{A}^T\mathbf{A})^{-1}(\mathbf{A}^T\mathbf{b}). \tag{12}$$

B. Centroid Localization

Centroid localization is a proximity based technique to determine the position of a BN with the help of certain RNs with minimum software efforts. A simple range-free implementation uses the link to a RN as sensor input for a rough location estimation [8]. In Fig. 5 a scenario with four RNs is shown. With the assumption of entire uniform circular communication ranges, the BN is located inside the shaded area when it has a link to all four RNs.

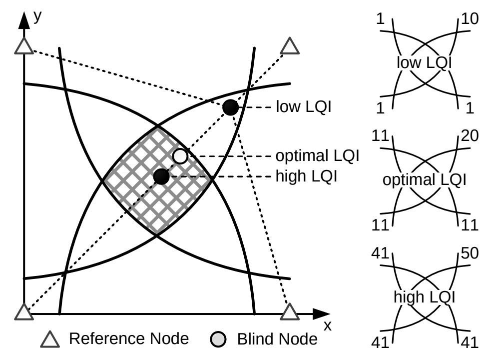

Fig. 5. Centroid localization approach showing the influence of the LQI distribution on the position estimation. Source: Own elaboration

The weighted centroid localization (WCL) approach uses a link quality indicator (LQI) like the RSS indicator (RSSI) to get a more precise location information [9]. The LQIs of several RNs are transformed into weights and the BN's position is given by the weighted positions of the RNs. The accuracy depends on the subfield of the regarding area (center or border) and the relationship between relative and absolute LQI values. For low LQIs the BN might be located near a dominating RN. For high LQIs the advantage of the weighting gets lost and the WCL reaches similar results to CL. In [1] we have proposed the selective adaptive weighted centroid localization (SAWCL) approach, which enables a further improvement of the accuracy by an adaption of the weights according to their statistical distribution. Looking at Fig. 5, for low LQIs all of the weights are raised by a specific fraction, for high LQIs they are reduced to increase the relative difference of the weights. The BN's two-dimensional position $P_i\,(x, y)$ at the time instant i is computed with the modified weights w'_{ij} and the fixed positions $B_j\,(x, y)$ of the RNs according to

$$P_i\,(x, y) = \frac{\sum_{j=1}^{n} \left(w'_{ij} \cdot B_j\,(x, y)\right)}{\sum_{j=1}^{n} w'_{ij}}. \tag{13}$$

IV. EXPERIMENTAL RESULTS

A one-dimensional tracking measurement is used to compare the LLS estimator and the SAWCL algorithm in terms of accuracy and complexity. The BN performs periodic movements on the motion test track according to the motion profile shown in Fig. 6. The duration of one movement from position A to B and back to A is $65\,\mathrm{s}$. For an explicit multipath propagation we installed metallic reflecting walls next to the track.

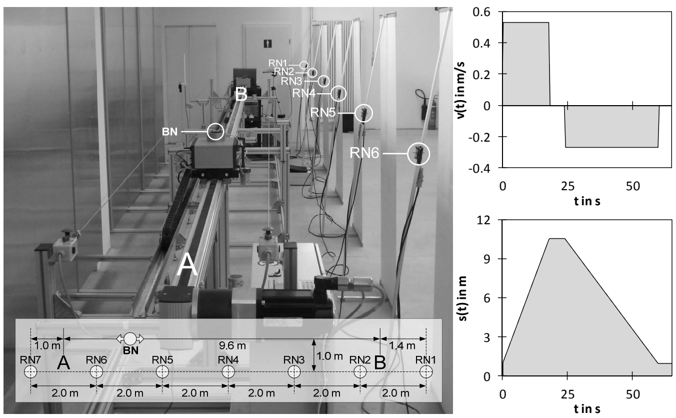

Fig. 6. Measurement setup on a motion test track in an obstructed test hall (velocity and position profiles show one A-B-A motion cycle, $T = 65\,\mathrm{s}$). Source: Own elaboration

To have a look at the location estimation error (LEE) we compare the CDFs of the LLS and SAWCL in Fig. 7. The corresponding values for the maximum, median and 95th percentile of the LEE are given in Table I. The median error of both estimators is below $0.72\,\mathrm{m}$. For a reliable tracking application it is necessary to have a look at the maximum error or at least the 95th percentile. The $LEE_{95\%}$ of the LLS estimator is three to four times higher than for the approximative SAWCL. At the same time the runtime complexity for the SAWCL calculations is nearly five times lower than for the LLS method.

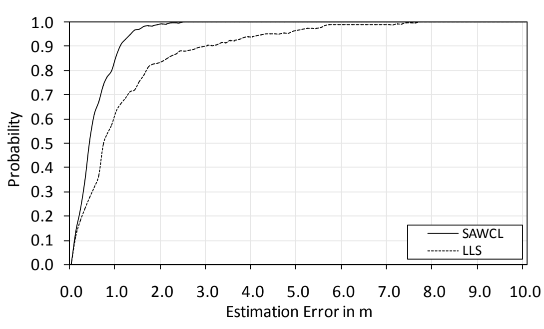

Fig. 7. Cumulative distribution functions for the location estimation error of a $9.6\,\mathrm{m}$ tracking measurements using the linear least squared error estimator (LLS) compared to the selective adaptive weighted centroid localization algorithm. Source: Own calculation

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT ESTIMATION TECHNIQUES (LEE - LOCATION ESTIMATION ERROR IN METERS, PERCENTAL RUNTIME COMPLEXITY RELATIVE TO THE SAWCL)

	LLS	SAWCL
LEE_{med}	$0.72\,\mathrm{m}$	$0.33\,\mathrm{m}$
σ_{LEE}	$1.37\,\mathrm{m}$	$0.43\,\mathrm{m}$
$LEE_{95\%}$	$4.25\,\mathrm{m}$	$1.29\,\mathrm{m}$
LEE_{max}	$6.24\,\mathrm{m}$	$1.85\,\mathrm{m}$
$Complexity$	$480\,\%$	$100\,\%$

V. CONCLUSION AND FUTURE WORK

The experimental results on the motion test track show the performance of the approximative SAWCL compared to the LLS approach. The significant advantage of the SAWCL benefits from the centroid approach. Hence, the unknown BN is always located on the line between the first and the last RN. With the LLS approach the BN position is often estimated outside the track, despite of the higher complexity of the LLS calculations. The measurement shows the importance of an adapted estimation strategy for error-prone distance estimations. Beside RSS measurements, also other range-based techniques using TOA or TDOA measurements could reach good results with the centroid localization approach.

Our further research focuses on the investigation of additional estimation techniques, e.g. the maximum likelihood estimator (MLE) or a Bayesian estimator using a Kalman filter. The experimental results of these techniques will extend the given comparison, whereas a more sophisticated comparison of the complexity – including runtime, memory space and communication overhead – will be used.

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