



SHORT COMMUNICATION

Accurate location estimation of sensor node using received signal strength measurements

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ABSTRACT

Received signal strength indications (RSSI) received at multiple anchors decay with distances that the signals have traveled to reach the sensors, so the sensor of unknown node can be uniquely located. By converting the nonlinear equations into linear equations the unconstrained least square calibration (ULSC) and constrained least square calibration (CLSC) algorithms are all algebraic closed-form solutions for RSSI-based wireless localization. The designed ULSC and CLSC algorithms obtain the corresponding best linear unbiased estimator by considering the anchor position uncertainty. The simulations demonstrate the validity of the localization computation method and test the impacts of signal strength noises on localization error. The results also show that the localization error of CLSC algorithm is less than that of ULSC algorithm and more close to the position Cramer–Rao low bound (CRLB) which provides optimal position accuracy.

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1. Introduction

Wireless sensor networks (WSNs) have been considered as a promising tool and have been used for various applications, such as habitat monitoring, environment monitoring, and target tracking [1]. Location information plays a crucial role in understanding the application context in WSNs [2–5]. Although sensor node localization plays an important role in all those systems, it is itself a challenging problem due to extremely limited resources available at each low-cost and tiny sensor node. Due to the constraints on hardware cost and energy consumption, however, it is unfeasible to equip all nodes with positioning hardware (e.g., GPS receivers). Instead, only a few nodes are configured with location information in the network setup phase, called anchors. Other nodes then locate themselves by the inter-node distance measurements [6–8].

Based on whether direct ranging measurement is required, there are basically two types of methods: range-free and range-based localization. Range-free localization mainly relies on the connectivity between nodes, network topology relationship to estimate the relative distance. The estimation error of range-free localization is relatively large in positioning accuracy. Compared with the

range-free localization, the hardware costs of range-based localization is higher, but it can obtain higher positioning accuracy. Range-based localization relies on accurate ranging measurement technology, such as Time of Arrival (TOA) [9,10], Time Difference of Arrival (TDOA) [11], Angle of Arrival (AOA) [12,13] or Received Signal Strength Indication (RSSI) [14,15]. There exist inherent tradeoffs between the localization accuracy and the implementation complexity of these ranging measurements, and the RSSI-based technique provides a low-cost and easy-implementation solution.

A number of localization algorithms became available for the ranged-based localization [16–19]. Maximum likelihood (ML) estimator can attain the approximate CRLB of positioning results. The cost function of the ML estimator is severely nonlinear and non-convex, so numerical solution of ML estimator strongly depends on the initialization. If the initialization is not sufficiently close to the global minimum, the numerical solution may converge to a local minimum or a saddle point causing a large estimation error. Therefore, determining an appropriate initialization point is a crucial problem in optimizing the ML cost function. As a result, some approaches have been introduced to address the shortcoming of ML problem. The semidefinite programming (SDP) in [20–23] by convex relaxation technique is a solution for the ML convergence problem. In the semidefinite relaxation technique, the nonlinear and nonconvex ML problem is transformed into a convex optimization problem. The advantage of SDP technique is that its cost function does not have local minima and thus convergence to the global minimum is guaranteed. The downside is that the SDP

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technique is sub-optimal and cannot achieve the best possible performance in all conditions. Based on many approximations the linear analytical solutions in [24–26] are proposed to obtain the algebraic solutions of the target positions.

In many circumstances, as described in the literature [27,28], the positions of anchors may contain errors and be uncertain. So the optimal position estimation of unknown node should be improved when considering the uncertain anchor positions. To reduce the positioning error, Vemula et al. [29] used Monte Carlo (MC) resampling method to obtain the optimal solutions of node positions considering the uncertainty of anchor positions, but the amount of calculation is very large and the positioning accuracy is greatly affected by the number of resampling times. The studies in [22,25] assume that the source transmit powers are the same and known. However the transmit power relies on its battery and antenna gain and might change with different sources.

In this paper, two algebraic closed-form algorithms are proposed for RSSI-based localization with known or unknown transmit power by considering the anchor position uncertainty. The unconstrained least squares calibration (ULSC) algorithm [18] reorganizes the nonlinear equations into a set of linear equations by introducing an extra variable that is a function of the positions. By exploring the relationship between the position and the auxiliary variable, the constrained least squares calibration (CLSC) algorithm improves the position estimate by using another weighted least square (WLS) computation. The rest of this paper is structured as follows. Section 2 presents the problem specification of RSSI-based localization. Sections 3 and 4 describe the algorithm design of RSSI-based localization with known and unknown transmit power. Section 5 analyzes the simulation results. The conclusion is represented in Section 6. This paper contains a number of symbols. Following the convention, we represent the matrices as bold case letters. If we denote the matrices as $(*)$, $(*)^{-1}$ represents matrix inverse. If $(*)$ contains noise, $(*)^0$ would denote its true value while $\Delta(*)$ is the noise component. $\mathbf{I}_{M \times M}$ and $\mathbf{1}_{M \times M}$ denote the M by M identity and the M by M one matrices.

2. RSSI model

In a two-dimension plane $\mathbf{x}^0 = [x^0 \ y^0]^T$ is denoted as the true position of unknown node to be determined and the true position of the i th anchor be $\mathbf{x}_i^0 = [x_i^0 \ y_i^0]^T$, $i = 1, 2, \dots, N$, where $N \geq 3$ is the number of anchors. The true distance between the unknown node and i th anchor, denoted by d_i^0 , is

$$d_i^0 = \sqrt{(x^0 - x_i^0)^2 + (y^0 - y_i^0)^2} \quad (1)$$

The signal strength through a radio channel is attenuated because of three nearly independent factors, namely, path-loss, shadow fading and multipath fading. The path-loss quantifies the attenuation of the transmitted power which decreases as d_i^0 increases. The shadow fading represents as low variation in a RSSI measurement due to obstacles in propagation paths. The multipath fading is caused by reception of multiple time delayed copies of a transmitted signal through multipath propagation and can be smoothed out by averaging the RSSI measurements over frequency and time. As a result, the average RSSI in dB measured at the N anchors, denoted by P_i , are

$$P_i = P_0 - 10\beta \log_{10} d_i^0 + n_i \quad (2)$$

where $i = 1, 2, \dots, N$, P_0 is the known transmit power in dB emitted from i th anchor, and β denotes the path-loss factor whose value varies from 1 to 5. In particular, $\beta = 2$ in free space. The n_i is called as shadow fading which is modeled as uncorrelated zero-mean Gaussian variable with variance δ_i^2 . It is assumed that the noise variance δ_i^2 is known via a calibration of the environment before deploying

these nodes. The goal of the localization problem based on RSSI measurements is to estimate \mathbf{x} given P_i , $i = 1, 2, \dots, N$.

ML estimator is asymptotically efficient meaning that it can achieve the CRLB accuracy when the number of measurements tends to infinity. The ML estimator of the measurement model in (2) is obtained by the following nonlinear optimization problem

$$\hat{\theta} = \arg \min_{\theta} \sum_{i=1}^N (P_i - P_0 + \log_{10} d_i^0)^2 \quad (3)$$

where $\theta = \mathbf{x}^0$ with known transmit power or $\theta = [\mathbf{x}^{0T} \ P_0]^T$ with unknown transmit power. Maximum likelihood (ML) solution to the localization problem can attain the position CRLB and be solved by Gauss–Newton or Levenberg–Marquardt (L–M). Based on a linear approximation to the target function Gauss–Newton or L–M method may fail when trapped in a local optimum. Even when the Gauss–Newton or L–M method converges, the solution may not be accurate because the convergence to incorrect local minimum may occur and ignoring the higher order terms in the Taylor-series expansion introduces significant error, as in the case when the measurement curves are approximately parallel. So an alternative approach to ensure global convergence is to reorganize the nonlinear equations into a set of linear equations.

3. Known transmit power

When the known transmit power is available, at least three anchor measurements are required for the positioning of an unknown node. Otherwise we cannot find a coarse estimate for the location of unknown node. The linear equations can then be solved straightforwardly by using least squares calibration (LSC) estimator.

Eq. (2) can be written as

$$d_i^{02} = 10^{\frac{P_0 - P_i + n_i}{5\beta}} \quad (4)$$

We linearize (4) by using a Taylor series expansion and neglect higher order terms when the variance δ_i^2 of noise is enough small. The right-hand side of (4) can be approximated using the first order Taylor series expansion as

$$d_i^{02} = \lambda_i + \frac{\lambda_i \ln 10}{5\beta} n_i \quad (5)$$

where $\lambda_i = 10^{\frac{P_0 - P_i}{5\beta}}$, $\frac{\lambda_i \ln 10}{5\beta} n_i$ is a zero-mean Gaussian random variable with variance $\frac{\lambda_i^2 (\ln 10)^2 \delta_i^2}{25\beta^2}$. Combining (1) with (5) we can obtain that

$$-2x_i^0 x^0 - 2y_i^0 y^0 + x^{02} + y^{02} = -x_i^{02} - y_i^{02} + \lambda_i + \frac{\lambda_i \ln 10}{5\beta} n_i \quad (6)$$

where $i = 1, 2, \dots, N$. When the position of anchor i contain error $\Delta \mathbf{x}_i = [\Delta x_i \ \Delta y_i]$ and the known position of the anchor is denoted as $\mathbf{x}_i = [x_i \ y_i]$, we can obtain that $\mathbf{x}_i = \mathbf{x}_i^0 + \Delta \mathbf{x}_i$. Substituting $x_i^0 = x_i - \Delta x_i$ and $y_i^0 = y_i - \Delta y_i$, (6) is rewritten as

$$\begin{aligned} -2x_i x^0 - 2y_i y^0 + x^{02} + y^{02} &= -x_i^2 - y_i^2 + \lambda_i \\ &+ \frac{\lambda_i \ln 10}{5\beta} n_i + 2(x_i - x^0) \Delta x_i + 2(y_i - y^0) \Delta y_i \end{aligned} \quad (7)$$

We denote the new unknown vector $\mathbf{z}^0 = [x^0 \ y^0 \ x^{02} + y^{02}]^T$, then the matrix solution equation constructed by stacking (7) in an ascending order of i is

$$\mathbf{A} \mathbf{z}^0 = \mathbf{b} + \alpha \quad (8)$$

where the row vectors of \mathbf{A} , \mathbf{b} and α are respectively equal to $[-2x_i \ -2y_i \ 1]$, $[-x_i^2 - y_i^2 + \lambda_i]$ and

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