RSSI Based Positioning Fusion Algorithm in Wireless Sensor Network Using Factor Graph

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Abstract. Various positioning techniques have been widely developed based on received signal strength indicator (RSSI) in Wireless Sensor Network (WSN) positioning systems. Multilateration-based positioning technique is simple and easy to realize, but it can not provide very high positioning accuracy caused by fluctuation of range measurement. Fingerprinting technique is a promising method benefitting from its high precision. However, the process of building radio map cost too much time and labor. In this paper, a fusion algorithm based on both multilateration and fingerprinting is proposed to reduce cost and maintain high accuracy at the same time. An adaptive radio propagation mode is presented in this algorithm as well as a multilateration approaches based on sparse fingerprint. Factor graph is adopted to fuse the results of these two positioning techniques. Simulation experiments demonstrate that the proposed positioning fusion algorithm performs much better than any of the original algorithms participated in the fusion process.

Keywords: Wireless Sensor Network (WSN) · Received Signal Strength Indicator (RSSI) · Fingerprinting · Multilateration · Fusion algorithm · Factor graph

1 Introduction

Location Based Services (LBS) are attracting more and more attentions. Although Global Navigation Satellite System (GNSS) performs very well in outdoor environment, it can work scarcely in indoor environment causing of the insufficient satellite coverage. In indoor localization, Wireless Sensor Network (WSN) positioning system is a good choice befitting from its low cost, easy implementation and high positioning accuracy. In WSN positioning systems, the location of unknown nodes is determined by anchor nodes [1].

There are two elementary kinds of positioning approaches frequently used in WSN positioning which are range based approaches and range free approaches [2]. In the range based approaches, multilateration technique is a key method to position the unknown node based on estimated distances between unknown nodes and anchor nodes. The distances are estimated by using some

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physical properties of communication signals, such as time-of-arrival (TOA), time-difference-of-arrival (TDOA), angle-of-arrival (AOA) and received signal strength indicator (RSSI) [3]. Precise synchronized clocks are required in TOA and TDOA, which is difficult to implement in practical applications. As AOA is easily influenced by the external environment and needs complex hardware devices, it is not only to increase the cost but also unsuitable for large-scale sensor networks. The radio propagation model is adopted in RSSI technique. The range between anchor node and unknown node is achieved by calculating signal propagation loss. Although it owns advantages of low cost and easy to realize, the positioning accuracy is worse than other approaches. The typical technique in range free approaches is fingerprinting which is also based on RSSI. There are two phases in fingerprinting. In the offline phase, the RSSI is collected at reference points (RPs) and then stored in a database named radio map. In the online phase, the target location is determined by comparing the rear-time collected RSSI with radio map using match algorithms such as KNN. Higher accuracy can be obtained by fingerprinting technique, however, the process of building radio map is a big challenge in terms of labor and time.

In this paper, a fusion positioning algorithm based on RSSI in WSN is proposed. The motivation is to deliver stable and precise position information in WSN by manipulating erratic and unstable RSSI signals [4]. The proposed algorithm is a combination of fingerprinting technique and radio propagation model based multilateration technique. A factor graph framework is used to achieve the final location information by fusing the positioning results from two positioning techniques. [5] proposed a kalman filter-based bybrid fusion approaches based on integration of fingerprinting and trilateration techniques, in which the radio propagation model is replaced by Euclidian distance formula to estimate distance. However, a radio map with high density is needed to achieve high positioning accuracy. In the proposed algorithm, only a sparse radio map is needed which reduces the workload of building radio map greatly. Under a factor graph framework, the proposed algorithm attempts to exploit the complementary advantages of these two algorithms to achieve a better positioning accuracy.

The remainder of this paper is organized as follows. Section 2 describes the proposed algorithms which include an adaptive radio propagation model, multilateration approaches based on sparse fingerprint and factor graph based fusion algorithm. In Sect. 2, several simulation experiments are conducted to verify performance of the proposed algorithms. Conclusions are given in the last section.

2 Proposed Algorithm

2.1 An Adaptive Radio Propagation Model

In the process of signal propagation, the overall effect results in lognormal distribution of received power at receiver. A general radio propagation model can be expressed as Eq. 1.

$$P(d) = P(d_0) - 10 \times \alpha \times \log_{10}(\frac{d}{d_0}) + \varepsilon \tag{1}$$

where $P(d)$ and $P(d_0)$ indicate the mean power received at reference distance d and d_0, respectively. $d_0 = 1\,\mathrm{m}$ is adopted in usual situations. The path loss exponent α is determined by environment. In free space, this exponent is selected as $\alpha = 2$. ε presents the noise caused by shadow fading and fast fading.

Based on the model, the distance d can be expressed as Eq. 2.

$$d = d_0 \times 10^{\frac{P(d_0)-P(d)+\varepsilon}{10\alpha}} \tag{2}$$

where ε is Gaussian distributed random variable with zero mean and variance σ_ω^2, $\varepsilon \sim N(0, \sigma_\omega^2)$.

In view of the system model, literature [6] proposed an unbiased estimator, in which the distance in the model is estimated as Eq. 3.

$$\hat{d} = d_0 \times 10^{\left(\frac{P(d_0)-P(d)}{10\alpha} - \frac{\sigma_\omega^2 ln10}{2(10\alpha)^2}\right)} \tag{3}$$

At the same time, the author presented a method to take multi-time ranging to restrain the fluctuation of RSSI. However, when the RSSI fluctuates very widely, it will lead to big deviation especially when the number of measuring times is not enough. To resolve this problem, an adaptive iterative algorithm is designed. During which, the σ_ω in Eq. 3 is self-updated through iteration step by step.

Algorithm 1. Adaptive Iterative Algorithm

Input
The set of measurement RSSI, $\{\varepsilon \sim N(0, \sigma_i^2)\}$;
Output
The estimated RSSI, $\{\varepsilon \sim N(0, \sigma_\Omega^2)\}$;
Initial
$\sigma_\Omega^2 = \sigma_0^2$;
while $\| \sigma_i^2 \| \neq 0$ **do**
$\sigma_i^2 = \frac{\sigma_i^2 \sigma_{i-1}^2}{\sigma_i^2 + \sigma_{i-1}^2}$;
end while
$\sigma_\Omega^2 = \sigma_i^2$;
Return σ_Ω^2;

Using the adaptive iterative algorithm, the fluctuation of RSSI is more gentle. The σ_ω^2 in Eq. 3 is replaced by σ_Ω^2. Then the estimate of $\hat{d}$ will be much more precision. The algorithm will be verified by the simulations in Sect. 3.1.

2.2 Multilateration Approaches Based on Sparse Fingerprint

Fingerprinting positioning technique is a combination of offline building radio map and online matching positioning. The offline phase is a training phase where RSSI fingerprints are collected to build radio map. In the WSN fingerprinting system, the network is usually divided into grids with the same size. The reference points (RPs) is located in the grids. The radio map is built jointly by the location coordinates and RSSI of all RPs. In a general way, the bigger the density of the radio map is, the higher the positioning accuracy will be. In online phase, the location of positioning target is determined by using matching algorithm. K-Nearest Neighbors (KNN) is the most popular matching algorithm in fingerprinting. The parameter K indicates the number of the nearest RPs to target point (TP). Supposing there are n RPs totally, the signal distance between TP and the ith RP is calculated as:

$$D_p = (\sum_{i=1}^{n} \mid TP - RP_i \mid^p)^{1/p} \tag{4}$$

when $p = 1$ and $p = 2$, the distance is named Manhattan distance and Euclidean distance, respectively. And the Euclidean distance is the most commonly used.

During fingerprinting process, the building of radio map with high density will cost too much time and labor. To overcome this problem, in this paper, a sparse fingerprint is proposed as shown in Fig. 1. RPs are presented by blue circles in the grids. From this figure, it can be seen that all of the grids are collected to be RPs in usual radio map. However, lots of the grids will be given up to be RPs in the radio map of sparse fingerprint. Taken the Fig. 1(b) and (c) as examples, the density of radio map is reduced greatly. The number of RPs is cut down more than half in the level-1 sparse radio map, further more, the level-2 sparse radio map is only one-sixteenth than usual radio map. Concurrently, the work load of building radio map is decreased with the same ratio.

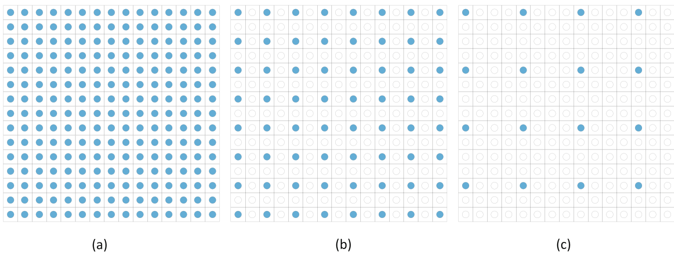


Fig. 1. (a) An usual radio map, (b) A level-1 sparse radio map, (c) A level-2 sparse radio map. (Color figure online)

Obviously, by using KNN algorithm, the positioning accuracy is worse when the density of radio map decreases. It is cased that the final positioning result is achieved by the average of RPs in KNN. In order to improve the positioning precision, a multilateration approaches based on sparse fingerprint (MASF) is proposed as followed.

The diagram of multilateration approaches is shown in Fig. 2(a). During multilateration in WSN, the location of unknown node is estimated only if not less than three anchor nodes can be used. The anchor nodes are arranged in fixed position in WSN.

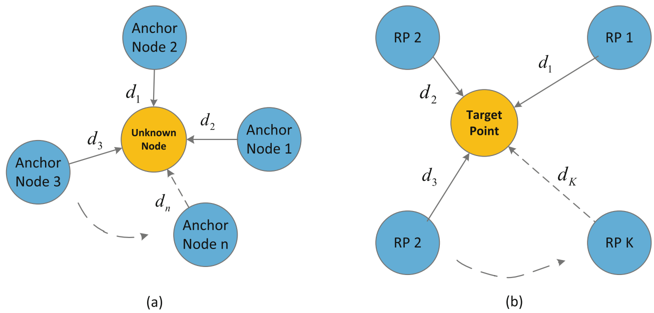


Fig. 2. (a) Diagram of multilateration approaches, (b) Multilateration in sparse fingerprint.

Based on KNN, we can get K nearest RPs with their location coordinates and RSSI. In MASF, as shown in Fig. 2(b), the selected RPs are considered as the anchor nodes. And the target point is considered to be unknown node. As the anchor nodes are replaced by RPs, there is no need to know the location information of anchor nodes any more, which is different with general WSN positioning. The distance between anchor nodes and unknown node is estimated by the adaptive radio propagation model which is shown in Sect. 2.1. Supposing that the coordinates of nearest RPs are $(x_j, y_j), j = 1, 2, ...K$, the distance between unknown node and the jth anchor node is indicated as $d_j, j = 1, 2, ...K$. The location coordinate of unknown node is assumed to be (x, y). Then we can get the formula as shown in Eq. 5.

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 = d_2^2 \\ \qquad\qquad \vdots \\ (x - x_K)^2 + (y - y_K)^2 = d_K^2 \end{cases} \tag{5}$$

After a series of mathematical transformations, the Eq. 5 can be transformed to be Eq. 6.

$$\begin{bmatrix} x_K - x_1 & y_K - y_1 \\ x_K - x_1 & y_K - y_2 \\ \vdots & \vdots \\ x_K - x_{K-1} & y_K - y_{K-1} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{2} \begin{bmatrix} (d_1^2 - d_K^2) - (x_1^2 + y_1^2) + (x_K^2 + y_K^2) \\ (d_2^2 - d_K^2) - (x_2^2 + y_2^2) + (x_K^2 + y_K^2) \\ \vdots \\ (d_{K-1}^2 - d_K^2) - (x_{K-1}^2 + y_{K-1}^2) + (x_K^2 + y_K^2) \end{bmatrix} \tag{6}$$

Let

$$\mathbf{A} = \begin{bmatrix} x_K - x_1 & y_K - y_1 \\ x_K - x_1 & y_K - y_2 \\ \vdots & \vdots \\ x_K - x_{K-1} & y_K - y_{K-1} \end{bmatrix}, \mathbf{X} = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\mathbf{B} = \frac{1}{2} \begin{bmatrix} (d_1^2 - d_K^2) - (x_1^2 + y_1^2) + (x_K^2 + y_K^2) \\ (d_2^2 - d_K^2) - (x_2^2 + y_2^2) + (x_K^2 + y_K^2) \\ \vdots \\ (d_{K-1}^2 - d_K^2) - (x_{K-1}^2 + y_{K-1}^2) + (x_K^2 + y_K^2) \end{bmatrix} \tag{7}$$

then we can get:

$$\mathbf{AX} = \mathbf{B} \tag{8}$$

or

$$\mathbf{X} = (\mathbf{A}^{\mathrm{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{B} \tag{9}$$

The unknown node lies at the intersection of all the circles. However, not only one point is intersected by all the circles caused by noise. To minimize the location error, the minimum mean square error (MMSE) technique is adopted to estimate the coordinate of unknown node.

Although only a sparse radio map is used in the proposed multilateration approaches based on sparse fingerprint (MASF), the positioning accuracy still maintains at a high level benefitting adopt the adaptive radio propagation model and multilateration technique. At the same time, the workload of fingerprinting positioning is reduced greatly. The performance of MASF will be verified in the simulation experiments.

2.3 Fusion Algorithm Based on Factor Graph

Factor graph is a relatively new modeling framework which has been used in a wide variety of applications. It is used for multi-source data fusion in wireless localization in [7]. In this paper, the KNN and MASF are considered to be two different fusion sources in WSN positioning. A better positioning result will be achieved by fusing these two positioning algorithm using factor graph. The core of factor graph is sun-product algorithm, which is shown in Fig. 3 in detail.

There are two kinds of nodes in factor graph named variable nodes and function nodes. The soft-information transmitted in factor graph can be expressed as:

$$\begin{cases} \mu_{x \to f}(x) = \prod\limits_{\mathbf{H}/x} \mu_{h \to x}(x), \\ \mu_{f \to x}(x) = \sum\limits_{\sim x} \{ f(\mathbf{Y}) \prod\limits_{\mathbf{Y}/x} \mu_{y \to f}(y) \} \end{cases} \tag{10}$$

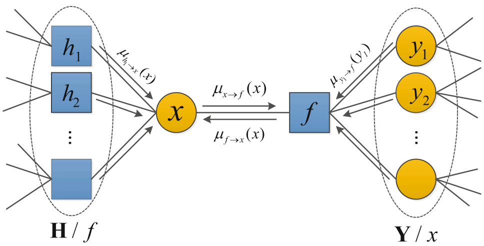


Fig. 3. Soft-information transmission rules in sum-product algorithm.

where x indicates variable nodes, f presents function nodes in factor graph. $\mathbf{H}/f$ denotes all the nodes connected to x other than f and $\mathbf{Y}/x$ means all the nodes connected to f other than x. $\mu_{x\to f}(x)$ and $\mu_{f\to x}(x)$ stand for the soft-information transmitted from x to f and from f to x, respectively.

Supposing that soft-information measurements satisfy Gaussian distribution with mean being m and variance being σ. The soft-information is defined to be I. Noted that the product of any Gaussian Probability Distribution Functions (PDF) is still a Gaussian PDF, the soft-information can be expressed as:

$$\begin{cases} I = \{m_I, \sigma_I\} \\ \prod_{i=1}^{k} N(x, m_i, \sigma_i^2) \propto N(x, m_I, \sigma_I^2) \end{cases} \tag{11}$$

where

$$\begin{cases} \frac{1}{\sigma_I^2} = \sum_{i=1}^{k} \frac{1}{\sigma_i^2} \\ m_I = \sigma_I^2 \sum_{i=1}^{k} \frac{m_i}{\sigma_i^2} \end{cases} \tag{12}$$

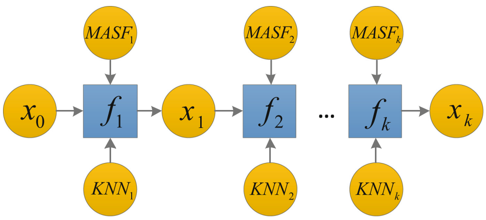


Fig. 4. Fusion structure model based on factor graph.

A fusion structure model is designed based on factor graph shown in Fig. 4. The KNN variable node and MASF variable node is fused in function node.

Based on the fusion structure model, the soft-information is obtained as shown in Eq. 13.

$$\begin{cases} I_{x_0} = \{m_0, \sigma_o^2\} \\ I_{x_1^0} = \{\frac{1}{1/\sigma_{K_1}^2 + 1/\sigma_{M_1}^2}(\frac{m_{K_1}}{\sigma_{K_1}^2} + \frac{m_{M_1}}{\sigma_{M_1}^2}), \frac{1}{1/\sigma_{K_1}^2 + 1/\sigma_{M_1}^2}\} \\ I_{x_1} = \{\frac{1}{1/\sigma_{x_0}^2 + 1/\sigma_{x_1^0}^2}(\frac{m_{x_0}}{\sigma_{x_0}^2} + \frac{m_{x_1^0}}{\sigma_{x_1^0}^2}), \frac{1}{1/\sigma_{x_0}^2 + 1/\sigma_{x_1^0}^2}\} \\ \vdots \\ I_{x_k^0} = \{\frac{1}{1/\sigma_{K_k}^2 + 1/\sigma_{M_k}^2}(\frac{m_{K_k}}{\sigma_{K_k}^2} + \frac{m_{M_k}}{\sigma_{M_k}^2}), \frac{1}{1/\sigma_{K_k}^2 + 1/\sigma_{M_k}^2}\} \\ I_{x_k} = \{\frac{1}{1/\sigma_{x_{k-1}}^2 + 1/\sigma_{x_k^0}^2}(\frac{m_{x_{k-1}}}{\sigma_{x_{k-1}}^2} + \frac{m_{x_k^0}}{\sigma_{x_k^0}^2}), \frac{1}{1/\sigma_{x_{k-1}}^2 + 1/\sigma_{x_k^0}^2}\}, \end{cases} \tag{13}$$

where $\{m_0, \sigma_o^2\}$ indicites initial input of fusion process. $\{m_K, \sigma_K^2\}$ and $\{m_M, \sigma_M^2\}$ present the positioning result of KNN and MASF, respectively. The fusion result is m_{x_k} as shown in Eq. 14.

$$m_{x_k} = \frac{1}{1/\sigma_{x_{k-1}}^2 + 1/\sigma_{x_k^0}^2}(\frac{m_{x_{k-1}}}{\sigma_{x_{k-1}}^2} + \frac{m_{x_k^0}}{\sigma_{x_k^0}^2}) \tag{14}$$

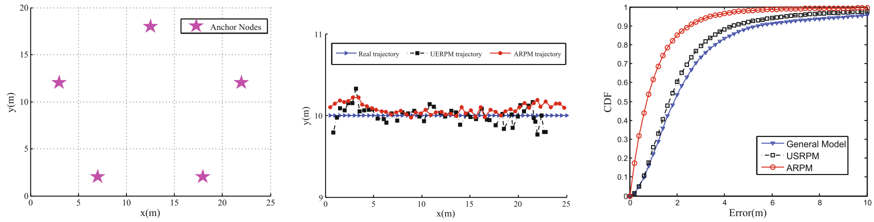
The location information of KNN and MASF are utilized adequately in the factor graph framework, which can improve positioning accuracy effectively.

3 Simulation Experiments

To verify the performance of the proposed algorithms, some simulation experiments are taken as follows.

3.1 Performance of Adaptive Radio Propagation Model

The simulation environment is established in a space of $25\,\mathrm{m} \times 20\,\mathrm{m}$ as shown in Fig. 5(a). The five anchor nodes are located at $(7, 2), (18, 2), (3, 12), (22, 12), (12.5, 8)$, which are shown with pink pentagrams. A contrast simulation experiment is conducted to illustrate the performance of adaptive radio propagation model (ARPM). As shown in Fig. 5(b), it can be seen that the trajectory of ARPM is much smoother, meanwhile it is more aligned with the real trajectory than the model used in [6] which we name it UERPM (Unbiased Estimator based radio propagation model). Figure 5(c) shows the cumulative distribution function (CDF) of the positioning error which is the root-mean-square error (RMSE) between the positioning results and the true coordinates. From the figure, it is clearly seen that both the ARPM and UERPM perform better than the general radio propagation model, meanwhile ARPM is more outstanding.

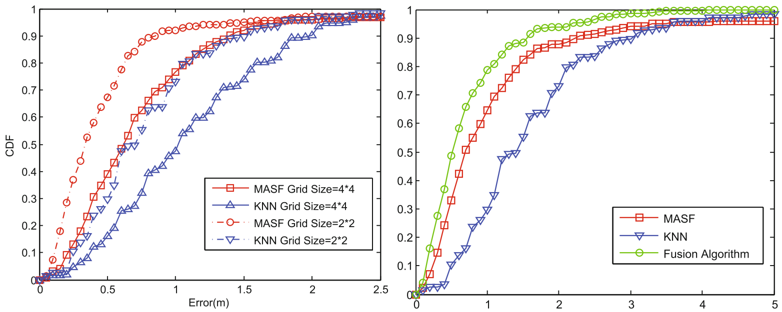


(a)Anchor Nodes Distribution. (b)Trajectory comparison. (c)CDF of UERMP and ARPM

Fig. 5. Performance simulation of adaptive radio propagation model

3.2 Performance of MAFS

The second simulation experiment is taken based on an actually measured radio map. The experiment is taken in 12*th* floor, 2A Building, Harbin Institute of Technology. Four CISCO AIR 1242 Access Points (AP) are adopted to build two kinds of radio map with grids size of $2 * 2\,\mathrm{m}^2$ and $4 * 4\,\mathrm{m}^2$, respectively. Compared to $2 * 2\,\mathrm{m}^2$ radio map, the $4 * 4\,\mathrm{m}^2$ radio map is considered to be sparse fingerprint. CDF of positioning error is used to demonstrate the performance of KNN and MASF. In the experiment, the parameter K is set to be 4. As shown in Fig. 6 (a), the proposed algorithm MASF performs much better than KNN obviously. Using the sparse radio map, the positioning accuracy within 1 m of MASF achieves 75%, while KNN is only 48%. The MASF using $4 * 4\,\mathrm{m}^2$ radio map performs basically the same as KNN using $2 * 2\,\mathrm{m}^2$ radio map. The fact that positioning accuracy can be improved by MASF is verified in this experiment.



(a)CDF of MASF and KNN (b)CDF of MASF and KNN

Fig. 6. Performance simulation of MASF and fusion algorithm

3.3 Performance of Fusion Algorithm Based on Factor Graph

In this simulation, the CDF is chosen to be evaluation criteria similarly. As shown in Fig. 6(b), taken positioning error within 2 meters as an example, the CDF of KNN, MASF and factor graph based fusion algorithm are 72%, 87%, and 95%, respectively. It can be seen that the fusion algorithm performs better than any fusion source.

4 Conclusion

A RSSI measurement based positioning fusion algorithm in WSN is proposed in this paper. An adaptive radio propagation model is presented to restrain the fluctuation of RSSI based range measurement. In addition, to improve the positioning performance more deeply, a multilateration approaches based on sparse fingerprint is proposed to reduce the cost of building radio map in fingerprinting technique. A fusion algorithm based on factor graph is proposed to fuse two different positioning algorithms of MASF and KNN. The fusion algorithm takes full advantages of both multilateration and fingerprinting techniques and outperforms conventional methods. Some simulation experiments are conducted to confirm performance of all the proposed algorithms.

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