Assuring Reliability of Localization Accuracy in Anchor-free Mobile Localization

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Abstract

Anchor-free localization algorithms do not depend on the existence of anchor objects. Since no anchor objects are required, the localization algorithm still can be applied in such problem as difficulty in distribution of anchor objects. In anchor-free localization problem, majority of the solutions need a specific requirement in order to achieve a high accuracy in their localization. In a real environment, it is difficult to maintain such environment. In this paper, we proposed the Distance Sequence for Mobile Localization (DSML) algorithm in order to estimate the position of sensor nodes based on the Receive Signal Strength (RSS) measurements. We exploit the relation of measured distance sequences and mobile beacon’s route to assure the reliability of the localization. We observed that about 89% of selected sensor nodes have improved for about 59% their localization error averagely.

Keywords: Wireless sensor networks, mobile localization, received signal strength

1. Introduction

Wireless Sensor Network (WSN) [1] is a collection of sensor nodes which are connected by wireless communication links. They are usually densely deployed in a wide area for object monitoring and target tracking. In various domains, such as volcanic eruption prediction [2] and disaster response [3], WSN has shown its significance and capability in application. WSN application is meaningful and can be responded to only if its position is known. When an abnormal events occurs, the sensor node needs the position information to locate the abnormal events. Indeed, sensor nodes are expected to know their positions for effective and efficient use of WSN.

Localization is an important fundamental problem dealing with how a sensor node determines its position coordinate. A straightforward solution is to equip each node with a GPS that can provide the node with its exact location. But this is not a cost-effective solution. It has limited applicability as well because GPS works only in open fields with no obstruction to satellite signals.

Hence, research attention has been attracted to beacon assisted localization in order to estimate the position of a sensor node. A mobile beacon receives signals from a sensor node and computes its location. There are two types of beacon distribution used to detect a sensor node. One is to deploy many fixed beacons which cover particular regions [4]. The number of beacons and their distribution thus has direct impact on the localization performance. A large number of distributed beacons will lead to better performance. But it will cost much if applied to a large area. Another way is to use a mobile beacon to do a location sensing. Since a mobile beacon is portable and easy to use, it is suitable for location sensing in a large areas (e.g. warehouse). In general, the reading range of a mobile beacon is around a few meters with an additional modular [5]. In the near future, the ability of mobile beacon will be improved due to new antenna designs. Therefore, the mobile localization method may become a widely used approach.

In this paper, we proposed the Distance Sequence for Mobile Localization (DSML) algorithm in order to estimate the position of sensor nodes based on the Receive Signal Strength (RSS) measurements. Distance sequence is a sequence of distances which are translated from the measured RSS by a mobile beacon. We assume that when a mobile reader travels between two points, they are travelling in a connection of multiple straight lines which lastly become one trajectory. In each straight line, a mobile beacon collects an RSS received from a node's messages in each interval time. The estimation of the position coordinate of a sensor node relies on the
estimation of distance between a sensor node and a mobile beacon by using RSS.

The rest of the paper is organized as follows: We investigate state-of-art anchor-based and anchor-less localization techniques which are described in section 2. The overview about Distance sequence for mobile localization (DSML) is presented in section 3. Section 4 describes the algorithm of that used in our localization. Our evaluation of performance is described in section 5 and are followed by conclusion in section 6.

2. Related Works

A large number of localization algorithms have been proposed. Majority of the algorithms assume the presence of anchor objects that know their exact positions in advance. Centroid [6] and MCL [7] directly receive location information from anchor objects and estimate its position. This assumption is problematic in many settings, particularly in the case where anchor nodes cannot be guaranteed to be fixed at known locations.

Meanwhile, anchor-free localization algorithms do not depend on the existence of anchor objects. Since no anchor objects are required, the localization algorithm still can be applied in such problem as difficulty in setting an anchor objects. Several anchor-free localization algorithms have been proposed. The incremental algorithm [8] usually begins with a selecting a small set of nodes and assigning coordinates to them. Then, each node uses the most recently computed coordinates neighbouring nodes to recompute its own coordinate repeatedly until the position of all nodes have converged. A drawback of this algorithm is that it is prone to error because of poor overall coordinate assignments. AFL algorithm [9] typically begins with an initial coordinate assignment based on the connectivity between nodes. Then, the mass-spring-based optimization is used in the next phase to improve the localization errors. The accuracy of this algorithm depends heavily on the initial coordinate assignments. Assigning a good initial coordinate is not easy, especially in the anisotropic topology which can be caused by the irregular shape of the area or by obstacles within the area.

In anchor-free localization problem, majority of the solutions need a specific requirement in order to achieve a high accuracy in localization such as good initial coordinate assignment [8, 9] or specific distances between neighbouring nodes [10]. In a real environment, it is difficult to maintain such environment. For example, even if the initial location was known, the final objects distribution may be different (e.g., moved by wind or people). Since there are no known objects to refer as a reference objects, the accuracy of estimated position cannot be assured. Many of solution for anchor-free localization have been proposed in the literature had achieved a great results in an experiment. Somewhat surprisingly, however, none of these solutions address the assurance of the estimation accuracy in a real environment.

Different from previous work, we proposed the reliable anchor-less localization techniques which exploited the relation of measured distance sequences and mobile beacon’s route. Our objective is to define the optimal accumulation of distance values to estimate the position of a sensor node by using the mobile beacon without deployment of any anchor objects. The main contribution of this paper is to guarantee the reliability of the localization without any information of anchor objects. Here, reliability indicates the consistency of our localization method to guarantee the credibility of the estimated coordinate of a sensor node. In order to assure the reliability of the localization, we characterize the relation between center coordinate of mobile beacon’s route with estimated coordinate in localization to distinguish the unreliable estimated coordinate. We evaluate the performance of our proposed algorithm by simulations.

3. Distance Sequence for Mobile Localization (DSML)

![Figure1: Communication Range](image)

We assume a mobile beacon travels in the sensory field boundary which have full of sensor nodes, transmitting their signals on a periodic basis. Each node has a unique ID. As shown in Fig.1, mobile beacon travels with a constant speed while collecting signals from sensor nodes in t interval time. We assume that a mobile beacon and sensor nodes are capable to communicate with each other within communication range D. Every time mobile beacon receives a message from a sensor node, it measures the RSS value of a message. Then it stores the tuple (t, r, ID) where ID denotes the ID of a node and r is a RSS value. We call this tuple as a node tuple.
Each tuple contains a different RSS value as they are collected from different position of mobile beacon in each $t$. Here, we call the multiple of a node tuple as a RSS sequence for one sensor node. Then, we translate RSS values into distances, $d$ in the sequence respectively which represents the distance sequence between a mobile beacon and a sensor node.

### 3.1. Conversion of RSS to distance

We exploit the accumulation of node tuples to estimate the position of sensor nodes. Clearly, the accuracy of position estimation depends on the RSS value in node tuple. In mobile localization, mobility and environment changes introduce additional effects such as small scale fading. Consequently, it is challenging to use RSS for an accurate localization. Therefore, we use fuzzy logic approach to interpret RSS in each node tuple into distance, $d$ to overcome these problems. Here, $d$ is a value which represents a distance between a mobile beacon and a sensor node. This approach interprets RSS input value into distance using a set of rules. It offers an inexpensive and robust way to deal with highly complex and variable models of noisy and uncertain environments using fuzzy logic [11].

RSS value is interpreted into fuzzy number, $\omega(x)$ by using a collection of discrete objects called fuzzy set. Fuzzy number is imprecise number rather than exact as is the single-valued numbers in fuzzy set which represents a degree of truth. Fuzzy set is defined by a truth value ranges in degree between 0 and 1. Here, we use the same fuzzy number function as described in [11] called triangular membership function as described below:

$$\omega(x) = \begin{cases} 
0, & \text{if } x < a \\
(x - a) / (b - a), & \text{if } a \leq x \leq b \\
(c - x) / (c - b), & \text{if } b \leq x \leq c \\
0, & \text{if } x > c 
\end{cases} \quad (1)$$

Rearranging and simplifying, we get

$$\omega(x) = \begin{cases} 
0, & \text{if } x < a \\
\frac{x - a}{b - a}, & \text{if } a \leq x \leq b \\
\frac{c - x}{c - b}, & \text{if } b \leq x \leq c \\
0, & \text{if } x > c 
\end{cases}$$

**Figure 2: Fuzzy set**

Here, $a$, $b$, $c$ is parameters in fuzzy set as shown in Fig.2. Input value is translated to get an output value which is approximate by using a fuzzy rule. Fuzzy rule is a form of IF-THEN statement that relates input and output variables. IF statement contains input variables of RSS value and the THEN statement contains output variables of distance, $d$.

In mapping process, an input of RSS value, $x$ intersects at two different fuzzy sets which give two different fuzzy number for each set as shown in Fig.3. Each fuzzy set has a fuzzy rule which translates the RSS fuzzy set to the distance fuzzy set as below:

1. **IF RSS is set $A$ THEN DISTANCE is set $A'$**
2. **IF RSS is set $B$ THEN DISTANCE is set $B'$**

Then we compute the center of gravity as $G = (G_a,G_b)$ of the trapezium formed at the distance fuzzy set. We compute the centroid of all $G$ as an output value for distance, $d$.

**Figure 3: Mapping Process**

### 3.2. Assuring Reliability of Localization

Fuzzy logic is not substantially affected to the environment changes such as number of nodes, irregularity in radio range and mobile beacon's velocity [11]. Hence, error of the translated distance from two RSS values are not significantly different if both RSS values are from the same real distances and sources (sensor node and mobile beacon).

However, it is difficult to ascertain the distance between sensor node and mobile beacon to be an equal in practice since all sensor nodes are deployed randomly. Therefore, in order to make an accurate estimation, it is important to select an appropriate $d$ to estimate the position of a sensor node.

For example, as shown in Fig.4(a), a mobile beacon travels around the sensor node field and measured a $d$ as described in subsection 3.1 as $d_1, d_2, ..., d_6$ for each interval time. To simplify the problem, we use a simple approach as described in [6] to estimate the position of sensor node $i$. This approach computes the position as the average of the reference coordinates in its vicinity.

Since we not assume the presence of reference objects, we use the coordinate of mobile beacon $M_1, M_2, ..., M_6$ as reference coordinates. Performance of this approach highly depends on the variation of distance from a sensor node to a mobile beacon coordinate. Assuming there are two selections of mobile beacon coordinates as shown in Fig.4(b), the estimation accuracy from Selection 1 is more accurate than Selection 2. The variation of distance...
in Selection 2 results a significant of error in localization of a sensor node. A balance of distance between a sensor node and each mobile beacon coordinates in Selection 1 reduce the variation of distance which contribute to higher accuracy.

However, it is unable to define the variation of distance in real environment since the real position of a sensor node is unknown. Therefore, in order to assure the reliability of the estimated coordinate, we evaluate the distance between estimated coordinate of a sensor node and the center coordinate of mobile beacon’s route. The less difference of the distance, the more accurate the localization.

Figure 4: (a) Variation of distance between a sensor node and each mobile beacon’s coordinate; (b) Localization of sensor node for each selection of mobile beacon’s coordinate.

4. Algorithm Description

In our proposed algorithm, we assume that a mobile beacon travels in a multiple of straight lines. In each straight line, mobile beacon collects and translates RSS values from a sequence of node tuples into a sequence of distance.

4.1. Construction of Distance Sequence

In our proposed algorithm, a mobile beacon receives a message from a sensor node i at time t and measures a d from a node’s message as \( D_{i,t} \). We assume that all sensor nodes are located in a static location. A mobile beacon travels in a same distance in each t and measures a distance \( D_{i,1}, D_{i,2}, ..., D_{i,n} \) where \( t=1,2, ..., n \). As shown in Fig.5, when mobile beacon moves from point A to point B, the distance values in a sequence does not seem to follow monotonic path and produce multiple of local minimum between these two points. This is a result from variation of RSS due to dynamic and unpredictable signal propagation. In DSML, we used the coordinate of a mobile beacon at the local minimum in a sequence to construct distance sequences in DSML. We define distance sequence as a combination of two kinds of sequences, \( D_{dec} \) and \( D_{inc} \). Here, \( D_{dec} \) is a sequence of distance which the values decrease monotonically and \( D_{inc} \) is a sequence of distance which the values increase monotonically.

Figure 5: Construction of distance sequence

To understand how the movement of a mobile beacon will constructs a distance sequence, we have to understand the affects to the distance when mobile beacon travel in its route. To focus on this affect, we consider an environment as shown in Fig.5 where a mobile beacon receives a RSS signal from a sensor node \( i \) and translates it into distance, \( D_{i,t} \). At time \( t=1 \), we compare the value of \( D_{i,1} \) at time \( t=1 \) and \( i=1 \). If \( D_{i,0} > D_{i,1} \), then we define \( D_{i,0} \) as a sequence of \( D_{dec} \). We continue this step until we find the \( D_{i,k} \) where \( D_{i,k} = D_{i,1} \) if \( D_{i,0} > D_{i,1} \) and \( i < D_{i,1} \).

In the definition of \( D_{inc} \), if mobile beacon moves \( s \) times after \( i \), we define \( D_{inc,s} \) as a sequence of \( D_{inc} \) if \( D_{inc,s} < D_{inc,s+1} \). Then, \( D_{dec} \) and \( D_{inc} \) are combined to construct a distance sequence, \( S = D_{dec,1}, D_{inc,1}, ..., D_{dec}, D_{inc,1}, ..., D_{inc} \) for one straight line. We continue this phase until the end of trajectory which construct a set of sequence in one trajectory as \( P_1 = \{ S_{1,1}, S_{1,2}, ..., S_{1,h} \} \) where \( h \) is a number of distance sequence for one trajectory.

4.2. Searching an Optimal Set of Distance Sequence

In this paper, we applied the Genetic Algorithm (GA) approach to search an optimal set of sequences. Genetic Algorithm (GA) is a search algorithm that searches an optimal solution to solve a combinatorial problem such as NP-complete Travelling Salesman Problem (TSP). In GA, the solution of given problem is represented as a chromosome. Then it creates a population of solutions and applies an operator such as mutation and crossover to evolve the solutions. Then the relative performance (fitness) of solution is compared in order to find the best solution.
Assuming we have in total $j$ of distance sequences in set $P_i$, we determine all sequences in set $P_i$ as an initial solution $P_i^{init} = \{S_{i,1}, S_{i,2}, ..., S_{i,k}\}$. We define the center of $P_i^{init}$ as $T_i$ computed from equation as below:

$$T_i = \frac{\sum_{l=1}^{q} p_{lt}}{q} \quad (2)$$

where $l=1,2,...,q$. Here, $p_{lt}$ is a mobile beacon’s coordinate which is a vertex of mobile beacon’s route in set $P_i$ and $q$ is a number of vertex points. We let $P_i^{init}$ represents the initial population in GA.

Since we are not using any anchor objects for our localization, we use the average of three coordinates of a mobile beacon which have biggest values of RSS as a localization. We use these information to compute the estimates coordinate $(X_i,Y_i)$ using Eq.(5)–Eq. (7) as shown below.

$$X_i = X_{i,tc}^{mobil} + (d \times \cos \theta) \quad (5)$$

$$Y_i = Y_{i,tc}^{mobil} + (d \times \sin \theta) \quad (6)$$

$$(X_i, Y_i) = \left( \frac{\sum_{k=1}^{j} X_{i,k}}{j}, \frac{\sum_{k=1}^{j} Y_{i,k}}{j} \right) \quad (7)$$

where $(X_{i,k}, Y_{i,k})$ is an estimated coordinate for $k$-th sequence, $S_{i,k}$ in set $P_i^{best}$ and $(X_{i,tc}^{mobil}, Y_{i,tc}^{mobil})$ is a mobile beacon when $i=tc$ in $S_{i,k}$. Here $d$ represents a distance $D_{tc}$ in $S_{i,k}$ and $k = 1,2,...,j$.

**Figure 6:** Computation of estimates position

5. **Experimental Evaluation**

In order to evaluate the performance of our proposed method, we carried out an experiment to determine the effectiveness of the proposed algorithm. We deploy 200 sensor nodes randomly in $10m \times 20m$ two dimension area as shown in Fig.7. We evaluate the error of estimated coordinates of sensor nodes using our proposed algorithm with a variation of node locations. In this experiment, one mobile beacon travels in fixed path which are known in advance. A mobile beacon travels in a constant speed and receives a messages from all sensor nodes in each interval time. We define the criterion for the localization error shows the degree of the estimation accuracy that the algorithm can perform. Each sensor node has poor estimation accuracy if it has large position error.

In the phase of searching an optimal set of sequences, we optimize a set of $P_i$ for each sensor node by searching
a set of sequences which has the closest of \( T_i \) to the reference coordinate, \( (X_i^{ref}, Y_i^{ref}) \). As shown in Fig.8, the distance between reference coordinate and \( T_i \) has improved for each sensor node for about 67% averagely.

We investigate the effect of optimization of set \( P_i \) on the localization accuracy of estimates coordinates, \( (X_i, Y_i) \) in localization by using non-optimize set of sequences and localization by using optimized set of sequences. Here, non-optimize set of sequences is a set which contains all sequences without searching the closest distance of \( T_i \) and reference coordinate. We characterize three interest values to simplify the explanation of our investigation as follows:

1) Value A: Difference of \( T_i \) and reference coordinate \( (X_i^{ref}, Y_i^{ref}) \).
2) Value B: Difference of \( T_i \) and estimates coordinate \( (X_i, Y_i) \).
3) Value C: Difference of estimates coordinate \( (X_i, Y_i) \) and real coordinate of sensor nodes which is also defined as a localization error of estimates coordinate.

We observed that not all sensor nodes improved their values B and there was an increment of values B in localization by using optimized set of sequences compare to the localization by using non-optimize set of sequences as shown in Fig.9 even though the center coordinates of optimized sequence were located near to reference coordinate. The increment was resulted from error in measured distance, \( d \) due to dynamic signal propagation which results localization error in estimates coordinates. Fig.10 shows the localization error of estimates coordinates by using our proposed method. We found that 65% of the sensor nodes have improved their localization error using an optimized sequence compared to the localization error using non-optimize sequence.

We study the relation of values A, B and C to verify if these values can be used to indicate the reliability of the localization. The reliable estimates coordinates are defined as a coordinate of \( (X_i, Y_i) \) who satisfy the following condition in their localization:

1) Decrement of values A in localization by using optimized set of sequences.
2) Decrement of values B in localization by using optimized set of sequences.

Fig.11 shows the values B of selected sensor nodes whose satisfy the condition as described above. The number of satisfied sensor nodes were 112 which is 56% from all sensor nodes. The average of values B has decrease for about 35% averagely in localization using optimized set of sequences. We observed that about 89% of selected sensor nodes have improved their localization error by using our method as shown in Fig.12. The average of values C has decrease for about 53% averagely in localization using optimized set of sequences.

![Figure 7: Experiment in variation location of sensor node.](image)

![Figure 8: Values A of sensor nodes](image)

### 6. Conclusion

We have proposed the distance sequence for mobile localization (DSML) algorithm based on the RSS measurement. We applied a Fuzzy logic to overcome the RSS-based localization problem. In this study, we demonstrated the reliability of our localization by distinguishing the unreliable estimated coordinates without using any information of anchor objects. The experiment results prove that not less than 89% of the selected sensor nodes improved for about 53% of their localization error averagely.

For further research, we suggest to investigate the characteristic of the sequence of \( P_i \) to improve the estimation accuracy and design a high assured localization technique in anchor-less localization system.
7. References


