

# Deploying Mobile Assisted Localization In Wireless Sensor Networks

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**Abstract**— In this paper we consider the problem of localization in wireless sensor networks and propose a distributed algorithm that helps unknown nodes to determine confident position estimates. The proposed algorithm is robust to range measurement inaccuracies and can be tailored to varying environmental conditions. The proposed position estimation algorithm considers the errors and inaccuracies usually found in signal strength measurements. We also evaluate and validate the algorithm with an experimental testbed. The test bed results indicate that the actual position of nodes are well bounded by the position estimates obtained despite ranging inaccuracies. The node localization problem in mobile sensor networks has received significant attention. We propose a fuzzy logic-based approach for mobile node localization in challenging environments. Localization is formulated as a fuzzy multilateration problem. For sparse networks with few available anchors, we propose a fuzzy grid-prediction scheme. The fuzzy logic-based localization scheme is implemented in a simulator and compared to state-of-the-art solutions. A hardware implementation running on Epic motes and transported by iRobot mobile hosts confirms simulation results and extends them to the real world.

**Index Terms**—Node localization, wireless sensor networks, mobility, fuzzy logic.

## I. INTRODUCTION

Wireless sensor networks (WSNs) are increasingly a part of the modern landscape. Disciplines as diverse as volcanic eruption prediction and disaster response benefit from the addition of sensing and networking. A common requirement of many wireless sensor network systems is localization, where deployed nodes in a network discover their positions. Wireless Sensor Networks, there can be

some GPS-enabled mobile nodes, called seeds, which can offer location information needed by other mobile nodes. But the number of seeds cannot be too many due to economic reason. In some earlier localization researches, seeds information is flooded to the whole networks, but apparently this is not efficient in mobile WSNs, because communication cost is too high, and after a long propagation, the information may be out-of-date or suffer from accumulated errors. Thus, we propose a novel localization approach, called Dynamic Reference Localization (DRL), which improves the DV-hop approach by deploying it locally. Instead of flooding all over the WSN, DRL reduces the overhead of flooding by dynamically limiting flooding in a local area, and keeps good performance by dynamic referencing. Dynamic referencing makes DRL a robust approach that can adapt to a wide range of nodes conditions, such as node speed, seed density, and node density. Since DRL runs in DV-hop manner, it does not need special (or expensive) hardware capable of detecting distance or angle that is required such as in . Moreover, DRL allows all of the nodes being mobile and moving freely, while there is only a limited fraction of nodes having self positioning capability.

DRL has the following characteristics:

- (1) Efficiency: Localization information is dynamically updated and flooded efficiently.
- (2) Robustness: Basically, DRL locates nodes by the triangulation technique; however, it also allows the situations if a node can not collect enough seeds for triangulation.
- (3) Special hardware free: DRL does not need any hardware of special capability.
- (4) Free mobility: DRL allows mobile nodes moving freely.

In some cases, localization is simple. For smaller networks covering small areas, fixed gateway devices and one hop communications provide enough resolution. GPS-based localization may be unreliable indoors, under forest canopies, or in natural and urban canyons. For example, GPS is used for high-precision asset tracking in but fails indoors. Signal strength-based solutions similarly fail when there is a high degree of RF multipath or requires dense network and assumes favorable conditions. All these solutions rely on stable environments with low multipath, where measured or sensed ranges (which are typically obtained by time of arrival, angle of arrival or received signal strength (RSS) techniques) reliably predict the actual distance between two nodes. For low multipath environments, accurate models have been proposed for estimating time of arrival, angle of arrival, and received signal strength. Mobility complicates the localization problem since node to node distance variations and environment changes (e.g., due to node mobility or interference from an external source) introduce additional effects, such as small-scale fading. Due to the relative motion between mobile nodes, each multipath wave experiences an apparent shift in frequency (i.e., the Doppler shift), directly proportional to the direction of arrival of the received multipath wave, and to the velocity/direction of motion of the mobile. Due to environment changes (i.e., objects in the radio channel are in motion), a time varying Doppler shift is induced on multipath components. Consequently, in such environments affected by small-scale fading, it is challenging to use simple connectivity (which itself can vary dramatically or Received Signal Strength for accurate localization). Fuzzy logic offers an inexpensive and robust way to deal with highly complex and variable models of noisy, uncertain environments. It provides a mechanism to learn about an environment in a way that treats variability consistently. These measurements are analyzed to produce rules that are used by the fuzzy inference systems (FIS), which interpret RSS input from unlocalized nodes and other anchors. The output of this process recovers the actual distance, compensated for variability in the local environment. This basic technique is employed in two constituent subsystems of FUZZLOC—the Fuzzy Multilateration System (FMS) and the Fuzzy Grid Prediction System (FGPS).

## II. A FUZZY LOGIC-BASED NODE LOCALIZATION FRAMEWORK

The challenges identified above were partially addressed in recent work in sensor network node localization. The authors create hybrid localization mechanisms that make use of range-based localization primitives (e.g., RSSI) to validate and improve the accuracy of range-free techniques. In a similar vein, we propose to formulate the localization problem as a fuzzy inference problem by using RSSI to obtain distance, in a fuzzy logic-based localization system where the concept of distance is very loose, such as “High,” “Medium,” or “Low.” The core intuition is that accurate ranges can be determined by learning about the local RF environment and developing rules based on this knowledge. Fuzzy logic provides a simple and computationally inexpensive way to accomplish this learning. In other, similarly dynamic scenarios like rail transportation and photovoltaic power generation, fuzzy logic provides mechanisms that allow simple systems to smartly adapt to rapidly changing environments.

In our proposed fuzzy logic-based localization system, distances between a mobile sensor node and anchor nodes are fuzzified, and used, subsequently in a Fuzzy Multilateration procedure to obtain a fuzzy location. In case two or more anchors are not available for performing localization using fuzzy multilateration, the sensor node employs a new technique, called fuzzy grid prediction, to obtain a location, albeit imprecise. In the Fuzzy Grid Prediction method, the node uses ranging information from any available anchor to compute distances to several fictitious “virtual anchors” which are assumed to be located in predetermined grids or quadrants. This allows the node to locate the grid/quadrant in which it is present. In conventional localization schemes, the location of a node is typically represented by two coordinates that uniquely identify a single point within some 2D area. Localization using fuzzy coordinates follows a similar convention. The 2D location of a node is represented as a Pair(X,Y), where both X and Y are fuzzy numbers and explained below. However, instead of a single point, the fuzzy location

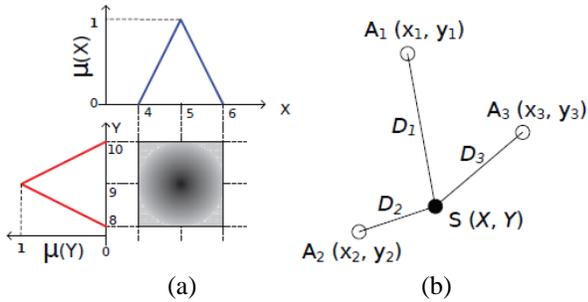


Fig.1. (a) Representation of a fuzzy location, using two triangular membership functions and (b) a sensor node S with fuzzy coordinates X and Y, to be located using three anchors at  $(x_1, y_1)$ ,  $(x_2, y_2)$ , and  $(x_3, y_3)$ .

represents an area where the probability of finding the node is the highest, as depicted in Fig. 1a. This section develops the theoretical foundation behind the computation of this fuzzy location, using imprecise and noisy RSSI measurements.

**2.1 Background**

Fuzzy logic revisits classical set theory and modifies it to have nonrigid, or fuzzy, set boundaries. Where classical set theory is concerned with collections of discrete objects, a fuzzy set, sometimes called a fuzzy bin, is defined by an associated membership function  $\mu$ , which describes the degree of membership  $0 \leq \mu(x) \leq 1$  of a crisp (regular) number  $x$  in the fuzzy set. The process of calculating the membership of a crisp number for many fuzzy sets is called the fuzzification process.

A fuzzy number is a special fuzzy bin where the membership is 1 at one and only one point. A fuzzy number represents a multivalued, imprecise quantity unlike a single-valued traditional number. One popular  $\mu(x)$  function, is the triangular membership function

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

where  $(a,b,c)$  defines a triangular bin. In this paper, we chose a triangular membership function because, in addition to being a good substitute for the more widely used Gaussian function, it has linear components only and computing membership is less resource intensive, suitable for our resource constrained sensor nodes. Since not all

triangular memberships are symmetric, we use the triangular function in its most general form. A comprehensive example can be found in Supplemental Material, available online, Section 1.

A fuzzy system translates a crisp input into a fuzzy output using a set of fuzzy rules which relate input and output variables in the form of an IF-THEN clause. Typically, the IF clause contains the input linguistic variable (e.g., RSSI) and the THEN clause contains the output linguistic variable (e.g., DISTANCE). An example rule is IF RSSI is WEAK THEN DISTANCE is LARGE.

**2.2 Fuzzy Multilateration**

We present fuzzy multilateration, a component of our fuzzy inference process, which obtains a node’s location from noisy RSS measurements, using fuzzy rule sets.

As shown in Fig. 1b, consider a node S that wants to be localized, in the vicinity of three anchor nodes  $A_j(j=1,3)$ .

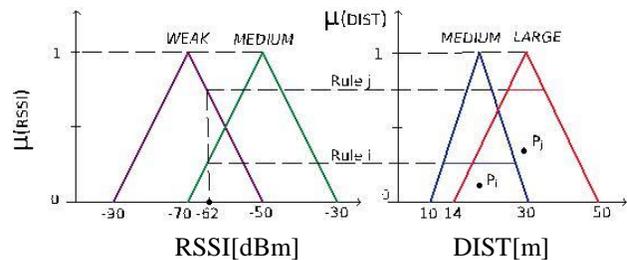


Fig. 2. The fuzzy inference process for an input RSSI value of  $\mu_{62}$  dBm. In this example, the fuzzy rule base maps this value through two rules: “Rule i” and “Rule j.” The dotted lines represent fuzzy inference: finding the membership (vertical line on left), applying the same membership to the output and defuzzification.

Each anchor node is equipped with a set of fuzzy rules that map fuzzy RSSI values to fuzzy distance values:

Rule i: IF RSSI is RSSI i THEN DIST is Dist i where RSSI i and Dist i are fuzzy linguistic variables (e.g., WEAK, MEDIUM, HIGH).

A fuzzy rule is created when two anchors can communicate directly. Since anchors know their locations, they can find the distance between themselves and also measure the RSSI. The anchors then fuzzify the crisp RSSI and distance values into two fuzzy bins RSSI i and Dist i respectively, through the process of fuzzification. The chosen fuzzy bin is the one in which the crisp value will have the highest membership value.

$$\begin{aligned}
 F_1 &= (X-x_1)^2 + (Y-y_1)^2 - D_1^2 = 0 \\
 \dots \\
 F_n &= (X-x_n)^2 + (Y-y_n)^2 - D_n^2 = 0
 \end{aligned}
 \tag{2}$$

The following defines a nonlinear system of equations describing the relation between the locations of the nodes and anchors and the distances among them.

**2.2.1 Fuzzy Inference**

A definition of the process of obtaining the fuzzy distance Dk between node and anchor is needed before solving the system of equations. As shown, an RSSI value of μ62 dBm has different membership values μ(RSSI) for the fuzzy bins WEAK and MEDIUM. The two fuzzy bins, in this example, are mapped by a fuzzy rule base formed by two fuzzy rules:

- Rule i: IF RSSI is MEDIUM THEN DIST is MEDIUM
- Rule j: IF RSSI is WEAK THEN DIST is LARGE

These two fuzzy rules define the mapping from the RSSI fuzzy sets to the DIST fuzzy sets.

$$D_k = (a,b,c) = \left[ \left( \frac{\sum L_n}{|L|} \right)_x, \left[ P_c \right]_x \right]
 \tag{3}$$

As shown in Fig. 2, the two fuzzy rules indicate the membership μ(DIST) in the DIST domain. Pi and Pj indicate the center of gravity of the trapezoid formed by the mapping of the RSSI into fuzzy bins MEDIUM and LARGE, respectively.

**2.3 Fuzzy Grid Prediction**

The multilateration technique presented in the previous section assumes the presence of a sufficient number of anchors, typically three or more. However, in mobile sensor networks with low anchor densities, it might frequently be the case that a node does not have enough anchors for multilateration. To address the problem, we extend our fuzzy logic-based localization framework to predict an area, e.g., a cell in a grid, where the node might be. A Virtual Anchor is a fictitious anchor which is assumed to be located at a known, fixed location in the field of deployment.

The distance to which can be found in an approximate way from the node. In FUZLOC, we place virtual anchors at the center of every square cell that the field is divided into, as described below. The key idea is that the nearer a node is to a virtual anchor, the more likely it is that the node can be found in that cell.

$$D_{SA2} = \min \left[ \overline{D_{SS1}} + \overline{D_{S1A2}}, \overline{D_{SA1}} + \overline{D_{A1A2}} \right]
 \tag{4}$$

The distances in (4) are fuzzy values, as the result of defuzzification by either A1 or A2 depending on the sender.

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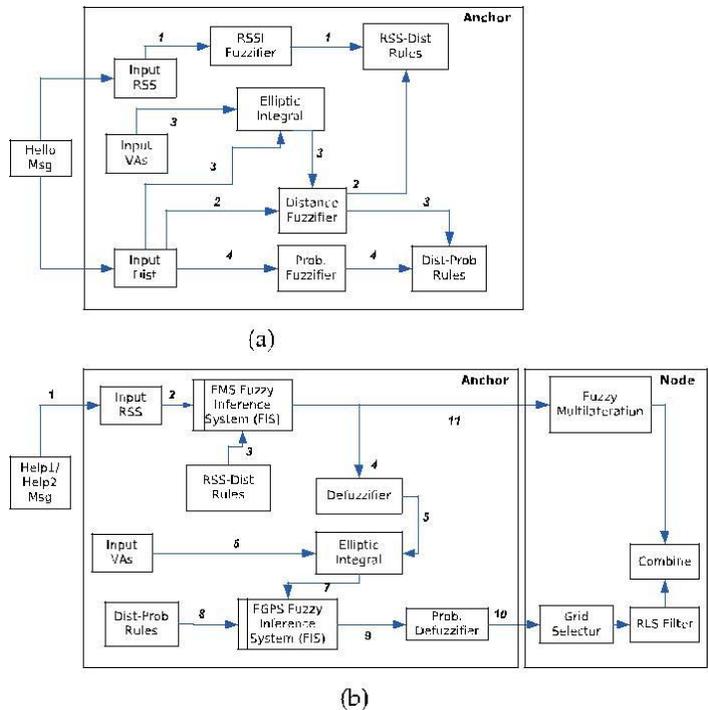


Fig. 3. The fuzzy logic-based localization system design with the(a) training and (b) localization phases

A numerical example for fuzzy multilateration can be found in Section 2 of the supplemental material, available Online. The key idea is that the nearer a node is to a virtual anchor, the more likely it is that the node can be found in that cell.

### III. PERFORMANCE EVALUATION

In this section, we first demonstrate that FUZLOC can be implemented and run on real mote hardware, then show FUZLOC's superior performance, when compared with state-of-the-art solutions like MCL, MSL, and Centroid. Owing to the relatively few number of robots, the difficulty in implementing MCL and MSL on real hardware (please note that neither MSL, nor MCL have been implemented/evaluated on real hardware), controlling the anchor and seed density and the physical space constraints, we decided to compare performance of FUZLOC with state-of-the-art solutions, in simulations using both empirical and synthetic data. In the remaining part of this section, we present FUZLOC implementation on real-hardware, describe the empirical and synthetic RSSI-Distance mapping, and performance evaluation results.

#### 3.1 System Implementation Validation

We implemented FUZLOC/FMS on EPIC motes running TinyOS 2.1.1. Since the matrices involved in FMS are not always square and hence they cannot be simply inverted, the fast and lightweight SVD-based pseudo inverse method was implemented on the motes. Relevant portions of the GNU Scientific Library (GSL) were ported to the MSP430 architecture in order to achieve this goal. The result was a fast method of inverting matrices, providing four digits of accuracy when compared to a similar computation on a desktop PC. The 1,574 lines of code fit comfortably in 18,726B.

A Fuzzy Inference System consisting of a triangular rule set and a center-average defuzzification method was implemented in 19,932B of ROM (including the code required to send and receive messages in the radio) and 1,859B in RAM on EPIC motes running TinyOS 2.1.1. Whenever a packet was received on the onboard radio, the detected RSS was applied to the prebuilt rule set and then defuzzified into a fuzzy distance. The distance and RSSI binset consisted of eight bins each. The defuzzified distance was equal to that produced by a similar computation on a desktop computer, within rounding errors. The execution time was less than 1 second. This proof-of-concept implementation

of FuzLoc on motes demonstrates its feasibility of implementation on a mote.

#### 3.2 Dynamic reference localization

The proposed *Dynamic Reference Localization* (DRL) mainly consists of two phases:

- (1) *Robust triangulation*: Every mobile node locates itself not only by regular triangulation, but also making use of other reference information it obtains.
- (2) *Seeds update*: Each of the seeds has its own parameters used to provide information for localization of other nodes.

##### Robust Triangulation:

A mobile node has to get three reference nodes, usually seeds, to do triangulation. However, it is not always that a node can get enough seeds information, especially when DRL limits the seed flooding scope to reduce network load. Therefore, according to the number of seeds information it gets, there are four cases described as follows.

For *three seeds case*, this is a normal triangulation situation (Figure 1(a)). For *two seeds case*, we can do triangulation with two seed circles and a velocity circle, as shown in Figure 1(b). A velocity circle is a circle, whose center is the previous estimated position of the target mobile node and its radius is the maximum distance a node can move in a time unit (i.e. maximum velocity that a mobile node can achieve, which is a given constant). For *one seed case*, we can estimate the position of the mobile node by averaging "the center of the intersection area" and "the current predicted position". The former can be estimated as the average of the two intersection points by the seed circle and velocity circle. And the latter can be derived by the most recent two estimate positions, supposing the mobile node is moving straight with the same speed they simply ask their next neighbors for help in the same way. Therefore, the inquiry will continue until it finds a node with seed information.

##### Seed update

Each seed in DRL has its own values of  $hd$  (hop-distance) and  $fh$  (flooding-hop) to reflect the current conditions around the seed. DRL has to update seeds dynamically to maintain its location correctness. When nodes are irregularly distributed,

such dynamic seed information is beneficial to location accuracy.

### 3.3 Anchor Density

Anchor density is a critical parameter for anchor-based localization schemes. Fig. 10b displays the impact of anchor density on the localization schemes where the number of anchors varies from 10 (32 anchors) to 50 percent (160 anchors), and the DoI is constant at 0.4. The accuracy of MCL and MSL deteriorates because an increase in anchor density is associated with an increase in the number of polluting sources. The mismatch of observed and actual radio ranges causes spurious anchors to appear as node's direct and indirect seeds. MSL considers nonanchor neighbors; hence, it experiences higher pollution. FUZLOC also has a decrease in localization error, with a larger number of anchors. We observe that FUZLOC is not significantly affected by DoI and ranging errors.

### 3.4 Node Density

For this performance evaluation scenario, we maintained the percentage of anchors fixed at 10 percent. The evaluated algorithms either suffer or are unaffected. None of the localization algorithms benefits from an increase in the node density. MCL considers indirect seeds for sampling; hence, a high node density means more anchors are misreported as indirect seeds. MSL considers nonanchor neighbors; hence, at high node densities, it experiences a huge amount of sample pollution. While non-anchor neighbors help MSL to improve accuracy at low DoI, they become harmful at higher DoI values.

### 3.5 Number of Bins

The number of bins in the fuzzy system is a design parameter—the greater the number of bins, the higher the accuracy of the system. As shown, as the number of bins increases, the localization error of FUZLOC decreases. This is because, more and more RSSs find a bin with high membership. The change in the number of bins is expected to not affect MCL, MSL, Centroid, or even Perfect FUZLOC experiences decreasing error with an increase in the number of bins

## IV. RELATED WORK

Localization in sensor networks can be defined as identification of sensor node's position. For any wireless sensor network, the accuracy of its localization technique is highly desired. Localization is the issue of

locating the geometrical position of the sensor node in the network. Localization problem is an estimation of position of wireless sensor nodes and to coordinate with one another. Localization is a challenge which deals with wireless sensor nodes and it has been studied from many years. There are different solutions and they are evaluated according to cost, size and power consumption. Localization is important when there is an uncertainty of the exact location of some fixed or mobile devices. One example has been in the supervision of humidity and temperature in forests and/or fields, where thousands of sensors are deployed by a plane, giving the operator little or no possibility to influence the precise location of each node. Therefore, the network localization problem, namely, the problem of determining the positions of nodes in a network, has attraction of many engineering field.

The device whose location is to be estimated is called localization node, and the network entity with known location is called localization base station. Wireless sensor network consists of a largest of inexpensive sensor nodes with wireless communication interface. These sensor nodes have limited processing and computing resources. Thus, algorithms designed for wireless sensor networks need to be both memory and energy efficient.

In most of the algorithms for wireless sensor network, it is assumed that the sensor nodes are aware of their locations and also about the locations of their nearby neighbors. Hence, localization is a major research area in wireless sensor networks. Nodes can utilize a global positioning system, but this solution is typically very costly. Many researchers are focusing on designing different algorithm but paying less attention on range measurement in accuracy. Localization is usually carried out by measuring certain distance dependent parameters of wireless radio link between the localization node and different localization base stations.

Many services are provided to users on the basis of location in wireless sensor networks. The role of location is very important in the wireless sensor networks. To access the data location is very important as the data itself. Location is also important for the upcoming areas such as mobile services, networks planning and sensor networks. There are considerable amount research activities to improve localization in wireless sensor networks. But there are also some

interesting open problems that need further attention.

#### V. CONCLUSIONS

Some localization schemes have fewer merits and greater demerits and some of them have less demerits and greater merits. These merits and demerits were the main source for proposing the idea of a unique approach which is the enhanced composite approach.

Localization problem is an open challenge in wireless sensor network. There are many aspects where we need improvements such as how to define threshold value in wireless sensor network. The performance of any localization algorithm depends on a number of factors, such as anchor density, node density, computation and communication costs, accuracy of the scheme and soon. All approaches have their own merits and drawbacks, making them suitable for different applications. Some algorithms require beacons (Diffusion, Bounding Box, Gradient, APIT) and some do not (MDS-MAP, Relaxation based localization scheme, Coordinate system stitching). Beaconless algorithms produce relative coordinate system which can optionally be registered to a global coordinate system. Sometimes sensor networks do not require a global coordinate system.

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