www.ijrream.in Impact Factor: 2.9463

INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)

Precise Information Share System on WSN Using Fuzzy Network Prediction Classification

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Abstract:

The node restriction issue in portable sensor systems has gotten critical consideration. As of late, molecule channels adjusted from mechanical technology have delivered great limitation correctnesses in ordinary settings. Disregarding these triumphs, cutting edge arrangements endure essentially when utilized in testing indoor and versatile situations described by a high level of radio sign anomaly. New arrangements are expected to address these difficulties. We propose a fuzzy logic based methodology for portable hub limitation in testing conditions. Restriction is detailed as a fluffy multilateration issue. For inadequate systems with scarcely any accessible stays, we propose a fluffy framework expectation conspire. The fluffy rationale based limitation conspire is actualized in a test system and contrasted with cutting edge arrangements. Broad recreation results show enhancements in the restriction exactness from 20 to 40 percent when the radio inconsistency is high. An equipment execution running on Epic bits and shipped by iRobot versatile hosts affirms reenactment results and extends them to this present reality.

Index Terms - Node restriction, wireless sensor networks, mobility, fuzzy logic

1. 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.

In some cases, localization is simple. For smaller net-works covering small areas, fixed gateway devices and one-hop communications provide enough resolution. Larger networks may be provisioned with location information at the time of deployment.

However, in many common environments, localization is more difficult. 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 interference. The solution proposed in relies on accurate measurement of RF TDOA and distance traveled and quickly degrades as accuracy decreases. Radio interferometry localizes nodes to within centimeters in but fails in multipath environments.

Mobile beacons roam an outdoor environment in but localization requires a 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. In one well-established fuzzy system, the Sendai railroad, fuzzy logic allowed the integration of noisy data related to rail conditions, train weight, and weather into acceleration and braking algorithms. Fuzzy logic can similarly be applied to localization. Empirical measurements are made between participating anchors in predictable encounters. 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 FUZLOC—the Fuzzy Multilateration System (FMS) and the Fuzzy Grid Prediction System (FGPS). The contributions of this paper are as follows:

We formulate the mobile node localization problem for noisy environments, as a fuzzy inference process. 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. We present a fuzzy grid prediction scheme, which optimizes our fuzzy inference process, under conditions of low anchor density. We demonstrate the feasibility of our proposed technique, through an implementation using mote hardware hosted on iRobot. We perform extensive simulations and compare our solution with state-of-the-art algorithms, using both real- world and synthetic data.

2. 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 Representation of a fuzzy location, using two triangular membership functions and a sensor node S with fuzzy coordinates X and Y , to be located using three anchors. Fuzzy location represents an area where the probability of finding the node is the highest, as depicted in Fig. 2. This section develops the theoretical foundation behind the computation of this fuzzy location, using imprecise and noisy RSSI measurements.

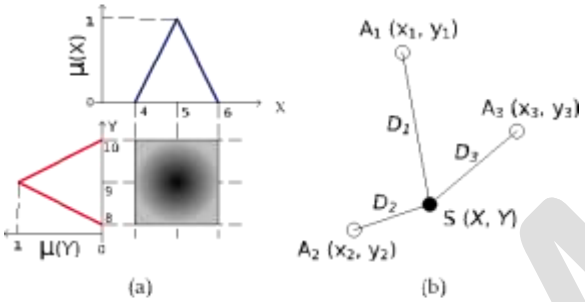

Fig. 2. Representation of a fuzzy location

3. 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, which describes the degree of membership 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 function, is the triangular membership function 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.

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

3.1 Fuzzy Multilateration

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 RSSIi and Disti respectively, through the process of fuzzification. The chosen fuzzy bin is the one in which the crisp value will have the highest membership value. For a more general case, when the node S is within radio range of n anchors, the node localization problem can be formulated as a fuzzy multilateration problem.

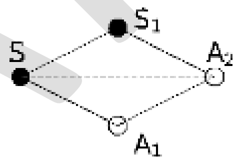

Fig 2. Fuzzy Multilateration

3.2 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. This process, called fuzzy inference, transforms a crisp Illustrating the multihop case for fuzzy multilateration: A node S localizes itself using A2 and A1. two fuzzy rules indicate the membership 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.

Typically, a single RSSI value triggers multiple fuzzy rules (the membership value of the crisp value in the input bin of the fuzzy rule is nonzero), resulting in multiple distance bins. Assume that the fuzzy rule base maps an RSSI value to a set of m fuzzy Dist bins. This definition of obtaining a fuzzy number through fuzzy inference produces a fuzzy number while giving more “weight” to the centroid by eliminating some possibilities at the edge. To truly represent the result one would need to compute a smooth and continuous function like the Gaussian membership function, but the triangular approximation has the advantage of reduced computation complexity. Limits its analysis to situations where the anchors and the node desiring localization are one hop from each other. This constraint limits the degree of accuracy that can be achieved. Two hops provide a good tradeoff between messaging overheads and accuracy as explained later. Consider an anchor A2 (Fig. 4) which is 2 hops away from a node S. Suppose that a regular node S1 and an anchor A1 are neighbors of both S and A2. The aim is now to find the distance DSA2. In a 2D space, a straight line between two points is also the shortest possible; hence, a good approximation is the minimum of all known distances between the two points. Applying this fact, we can now calculate

RSSI value obtained from a packet sent by a node and received by an anchor into a fuzzy number Dk. has different membership values for the fuzzy bins W EAK 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 W EAK THEN DIST is LARGE

4. LOCALIZATION SYSTEM DESIGN

The node localization system (called FUZLOC) that implements the proposed fuzzy logic-based localization frame-work is depicted in Fig. 6. As shown, the localization system runs on both anchor and sensor nodes.

Training happens with the participation of anchors only, while the localization phase involves both anchors and nodes. The components required for the fuzzy multilateration subsystem, as well as the fuzzy grid prediction subsystem are implemented on both anchors and nodes. The fuzzy rules required for these subsystems are created during the training phase. Anchors are assumed to have more computing power than ordinary nodes; they can then maintain these fuzzy rules.

The FUZLOC localization system uses two types of messages a HELLO type message which anchors use to train the localization system (i.e., anchors broadcast their location and build rules), and a HELP type message which nodes use for localization (i.e., nodes notify 1-hop and 2-hop anchors and nodes that they need to localize).

The remaining part of this section describes the localization system training and its use of HELLO.

4.1 Localization System Training

The training of the localization system takes place every time two anchors come within communication range with each other. The anchors know their locations, hence, an anchor can compute the distance between it and the other anchor. The key observation here is that since an anchor can also measure the RSSI of an incoming message, it can build the fuzzy rules required for both FMS and FGPS. Fig. 6a depicts the training phase where a single HELLO message is used to the build the rule sets for both FMS and FGPS.

FMS Training. Anchors exchange HELLO messages (Algorithm 1, step 2). As shown in Fig. 6a, the RSS of an incoming HELLO message (“Input RSS”) is fuzzified by choosing the fuzzy set with the highest membership ðRSSI Þ (Fig. 6a, Path 1). The distance between anchors (“Input Dist”) is fuzzified into a distance fuzzy set (Fig. 6a, Path 2). The result of the training populates the rule base, i.e., “RSS-Dist Rules”.

FGPS—Training. When an anchor receives a HELLO message, it calculates the distances between the sender and each virtual anchor, using (14) (Path 3). This calculation is shown in Algorithm 1, step 9. These distances are then fuzzified (“Distance Fuzzifier,” Path 3). Additionally, the probabilities for the anchor being in each grid are updated, as shown in Algorithm 1, step 10.

4.2 Localization Protocol

The localization phase which runs on both anchors and nodes is shown in Fig. 6b. In order to obtain its location, a node sends a HELP2 message (Algorithm 2, step 2). A HELP2 message is meant to trigger actions in nodes/ anchors which are 1-hop away. These nodes/anchors perform some calculations (explained below), then re-broadcast a HELP1 message, meant to trigger actions in the 2-hop anchors.

5. CONCLUSIONS

We have proposed FUZLOC, a fuzzy logic-based localization method suitable for wireless sensor nodes that are mobile in noisy, harsh environments. The constituent systems use fuzzy multilateration and a grid predictor to compute the location of a node as an area. The RSS is cast into bins which encode the imprecision; these bins are subsequently used in our mathematical framework. We remark here that the case of static anchors, considered by neither MCL, nor MSL, will be investigated in future work.

Our method has been evaluated based on a variety of metrics. They prove that our method is resistant to high DoI environments while providing a low localization error without any extra hardware. Only anchors need to have a slightly higher storage requirement. A deployment with more anchors at high DoI decreases the error. The ability to localize using both single-hop and two-hop anchors greatly increases the variety of topologies where localization succeeds. The system implementation proves that the algorithm functions well on resource constrained devices.

REFERENCES:

[1] G. Werner-Allen, K. Lorincz, M. Ruiz, O. Marcillo, J. Johnson, J. Lees, and M. Welsh, “Deploying a Wireless Sensor Network on an Active Volcano,” IEEE Internet Computing, vol. 10, no. 2, pp. 18-25, Mar./Apr. 2006.

[2] S. George, W. Zhou, H. Chenji, M. Won, Y.O. Lee, A. Pazarloglou, R. Stoleru, and P. Barooah, “DistressNet: A Wireless Ad Hoc and Sensor Network Architecture for Situation Management in Disaster Response,” IEEE Comm. Magazine, vol. 48, no. 3, pp. 128-136, Mar. 2010.

[3] T. He, S. Krishnamurthy, L. Luo, T. Yan, L. Gu, R. Stoleru, G. Zhou, Q. Cao, P. Vicaire, J. Stankovic, T. Abdelzaher, J. Hui, and B. Krogh, “VigilNet: An Integrated Sensor Network System for Energy-Efficient Surveillance,” ACM Trans. Sensor Network, vol. 2, no. 1, pp. 1-38, 2006.

[4] D. Balakrishnan, A. Nayak, P. Dhar, and S. Kaul, “Efficient Geo- Tracking and Adaptive Routing of Mobile Assets,” Proc. IEEE Int’l Conf. High Performance Computing and Comm. (HPCC), 2009.