A NOVEL APPROACH FOR RANGE FREE LOCALIZATION IN WIRELESS SENSOR NETWORKS

Dissertation submitted in fulfillment of the requirements for the degree of

MASTER OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

By

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April, 2017

PAC FORM

TOPIC APPROVAL PERFORMA

School of Computer Science and Engineering

Program : P172::M. Tech. (Computer Science and Engineering) [Full Time]

COURSE CODE : CSE545 REGULAR/BACKLOG : Regular GROUP NUMBER : CSERGD0023

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Qualification : ____________________ Research Experience : ____________________

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PROPOSED TOPIC : A novel approach for range free Localization in Wireless sensor network

Qualitative Assessment of Proposed Topic by PAC		
Sr.No.	Parameter	Rating (out of 10)
1	Project Novelty: Potential of the project to create new knowledge	6.83
2	Project Feasibility: Project can be timely carried out in-house with low-cost and available resources in the University by the students.	7.00
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ABSTRACT

Numerous applications such as Internet of Things and robotics using sensors and Wireless Sensor Networks (WSN) require localization and target tracking for their efficient implementation and functioning. Localization means determining the precise position of nodes within the network. Localization sometimes, is also a precondition to other functionalities such as routing, self-organization capability etc. Various approaches and algorithms have been proposed to solve the localization problem. Most of these techniques involve use of some deployed nodes whose position coordinates are already known to us (using GPS or some other method) called landmarks or anchors. This study attempts to leverage the imprecision and uncertainty handling ability of soft computing techniques such as Fuzzy Logic. An aggregated Mamdani- Sugeno Fuzzy Inference System based localization approach has been proposed using triangular membership functions. One input (RSSI), 5 rules and one output (weight) model has been implemented. The output weight indicated the proximity of a particular anchor to an unknown node. The weight was then used in weighted centroid to compute the estimated position of the unknown sensor node. The solution was optimized using Gauss Newton method. The accuracy of the proposed scheme was several times better than centroid, weighted centroid and some other works done using soft computing techniques.

Keywords: WSN, Anchors, Range-Free, Sugeno Fuzzy Inference Systems, Mamdani Fuzzy Inference Systems, Localization algorithms, Gauss Newton method

DECLARATION STATEMENT

I hereby declare that the research work reported in the dissertation entitled "**A NOVEL APPROACH FOR RANGE FREE LOCALIZATION IN WIRELESS SENSOR NETWORKS**" in partial fulfilment of the requirement for the award of Degree for Master of Technology in Computer Science and Engineering at Lovely Professional University, Phagwara, Punjab is an authentic work carried out under supervision of my research supervisor **Mr. Deepak Prashar**. I have not submitted this work elsewhere for any degree or diploma.

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ACKNOWLEDGEMENT

No research can be done in an isolated environment and this, certainly was not an exception. It was a concerted effort of all my friends, family and above all me. I would like to thank everyone from core of my heart.

I would like to express the deepest appreciation to my mentor, **Mr. Deepak Prashar**, who has the attitude and the substance of a genius. He always helped to clear all doubts generated during different parts of this literature review and formulation of statement for my research work. His guidance is also a motivation for me to do work on time. His guidance was crucial for formulation of problem statement and carry forward approach.

SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the M.Tech Dissertation entitled "**A NOVELAPPROACH FOR RANGE FREE LOCALIZATION IN WIRELESS SENSOR NETWORKS"**, submitted by **Abhishek Kumar** at **Lovely Professional University, Phagwara, India** is a bonafide record of his original work carried out under my supervision. This work has not been submitted elsewhere for any other degree.

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CHAPTER 1

INTRODUCTION

Wireless sensor networks are defined as a network of tiny sensor nodes. These sensor nodes are deployed in the field independently and they operate coordinately through wireless links. There might be different kinds of sensor nodes in a network, some nodes with basic functionalities and some with expensive special functionalities. The network may be distributed over a small field, in a household, in an industry, or it can be an operating over a large forest, deep oceans, or a traffic monitoring network in a city. Wireless sensor networks are not limited by the type of data they monitor [1]. The data can be seismographic readings or humidity levels or sounds in the forest or traffic camera recordings of a city.

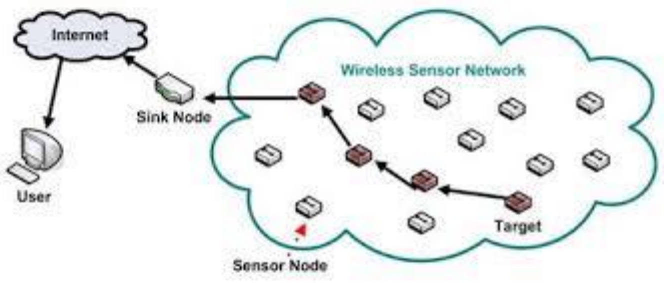

Figure 1: Basic Organization of Sensor Network

Wireless sensor networks have become cost effective and small in size, thanks to the speed of evolution of technology. Flexibility, Scalability, Accuracy of sensor networks have made its manufacturing rapid, which in turn reduced the cost of development. Deployment of monitoring nodes has become simple with robust and reliable low cost nodes.

Sensor networks cannot have a single design because, incorporating all the features in one design makes the nodes costly and size cannot be small. Design of wireless sensor networks has become application specific as the requirements are different in each application. A military application demands secure communication, A healthcare application demands accuracy, An environmental monitoring scheme demands for robustness, A traffic monitoring scheme demands for longer lifetime. This might be the reason that the sensor networks are attracting attention of researchers to address these design constraints, improving existing protocols.

Wireless sensor networks just like Ad-hoc networks are subjected to the challenges such as Limited power, limited coverage area of a node, no existing infrastructure, security issues, and interference to communication, channel restrictions, Congestion etc. Several surveys in wireless sensor networks stated research domains such as routing techniques, MAC protocols, data congestion control, data aggregation, energy conserving mechanisms, localization, and security. And in addition there were many application domains such as medical, and environment monitoring. WSN has umpteen number of applications in health, military, security, disaster prevention and weather forecasting.

1.1 Architecture and Design

The underlying architecture assumes significance in backdrop of deploying large number of sensor nodes that need to be lost cost, low power consuming, have less processing ability and small in size. This is accomplished using ASICs (Application Specific Integrated Circuits). AISC provides a cost effective solution for sensor nodes such as MICA2 that need minimal power consumption.

Typically a sensor node can be considered to have four principal components: Communication component for data dissemination; Computing component for information gathering and processing; Sensing component consisting of analog to digital converters to detect an event; and Power component for power supply. A diagrammatic representation is shown in following Figure 2 [1]:

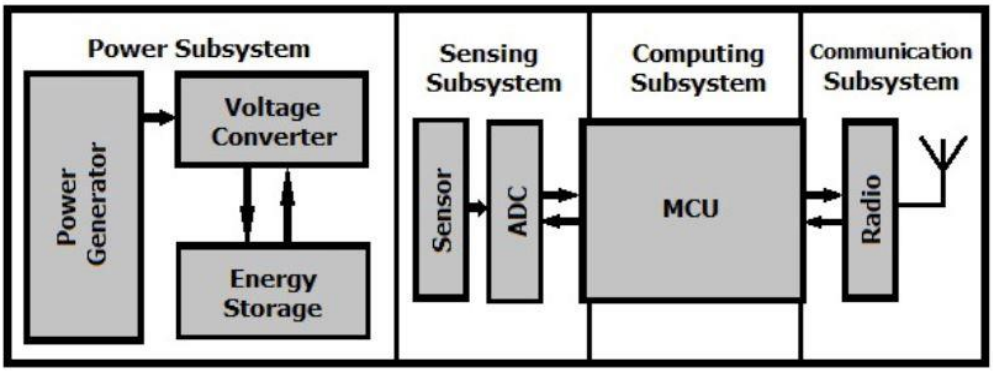

Figure 2: Sensor Node components

The Micro control Unit (MCU) is the brain of the sensor node performing various operations and processing on the data and information gathered. It further provides an interfacing options with IDEs such as Arduino^{TM}.

1.2 Localization in WSN

Localization is referred to the process of identifying the location of sensors with the help of anchor/beacon nodes. Wireless sensor networks as stated above, have limited resources. All the sensor nodes cannot have location awareness independently as they are deployed in ad hoc manner in the network and some other factors such as cost, power constraints, size etc. In some cases, the GPS systems cannot be employed as the environmental conditions restrict the communication with satellites. Eg:- monitoring applications in deep forests, ocean depths, household application in case of basements and dense concrete structures. Location of sensor node is very important in many applications. Without the location information, the data collected is of no use. Thus the sensor localization is an important domain in WSN. Mobility is an important indicator of development. Mobile sensor nodes are required to have location awareness.

To determine the location of all the sensor nodes in the network, we some nodes in the network that must be self-aware of their own position either by placing them in a fixed known location or by providing them with GPS like systems. These nodes are referred to as Anchor/Beacon nodes.

A sensor node to identify its own location, it communicates with the in-range anchor nodes. The beacon signals send the location of beacon nodes. The sensor nodes find the distance and/or angle between anchor node and sensor node. From all the information of anchor nodes' locations and distances, sensor nodes calculate their own location.

1.2.1 Factors Affecting Localization

Localization, in this context can also be inferred as self-localization that is nodes are able to localize themselves without any human interference. Localization process is often a subject of various aspects which are summarised as:

A) Node density

Most of the localization algorithms are dependent on number or density of nodes that are to be monitored and are to be localized. However, the approaches which depend on counting the hops or estimating the distance are not vitally dependent on node density. Also with a significantly high number of nodes, cost trade off can also become an important factor. High density can also lead to a larger transmission and propagation delay. So a trade-off on number of nodes versus cost and total latency must be considered while deciding a localization algorithm.

B) Topology and adaptability

Topology refers to physical organisation of a sensor network in the area of deployment or monitoring. In networks comprising of concave S or C topologies , using Euclidean approach to calculate distance between two nodes is not a good idea [2]. Some localization algorithms are not able to successfully localize nodes on boundaries of networks because of poor quality distance data gathered and thus the localization results are absolutely corrupted. Thus it matters whether the topology [3] either S or C shaped as shown in Figure 3 is suitable for a particular localization approach.

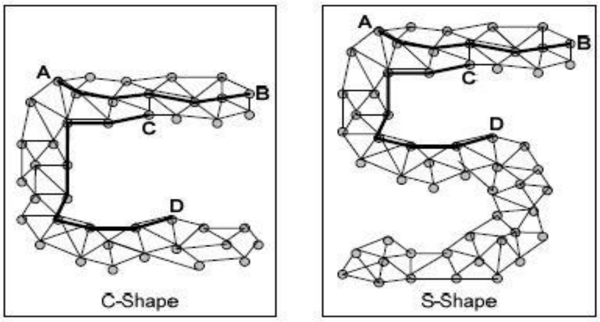

Figure 3: Type of Topologies

C) Limited availability of resources

With the advancements in VLSI and fabrication techniques, the sensor nodes are getting smaller and smaller. Thus the resources at their disposal for example battery power, storage capacity, processing capability are getting reduced. The localization algorithm must be able to deal with limited availability of resources and still be able to produce accurate position estimates.

D) Obstacles and irregular deployment area

Presence of obstacles or an irregular deployment area can affect the localization process. One of the assumptions in wireless sensor networks is to have a line of sight communication within the nodes. Obstacles or hurdles may cause diffraction and deflection of signals and thus incorrect estimation leading to an inaccurate result.

E) Mobility

Initially the sensor networks were designed with nodes being static or stationary. But with requirement of new applications such as Internet of Things, the network became mobile. The localization algorithm must be adaptable and deal with mobility of nodes: either anchors or targets or both. The idea is to exploit mobility as an advantage rather than considering it as a burden. Presence of mobile nodes can overcome various shortcomings such as: low density, presence of hurdles or obstacles, S or C shaped topology etc.

Mobility in wireless sensor networks can be modelled using various techniques such as Random Way Point (RWP) in which each sensor node moves independently by choosing a random destination and a random speed; Random Walk model in which a sensor node moves independently with random speed and direction. Unlike RWP, choosing of destination does not happen in this case. In the contrast, smooth models are deterministic and the movement can be tracked mathematically. Gauss Markov mobility model is a smooth model, detailed description of which has been provided in **Appendix A**. A somewhat uniform model is Random Direction in which a node moves with random direction and speed until it encounters an edge and then repeats the same process as shown in the Figure 4 :

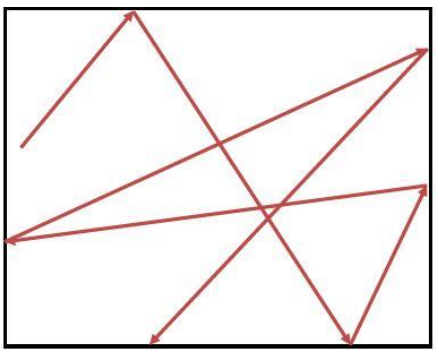

Figure 4: Random Direction Mobility Type

[Image Courtesy: nptel@iitm.ac.in]

1.2.2 Distance Estimation

Any basic localization procedure consists of three mains steps: First, distance estimation; Secondly, position estimation; and then at last localization algorithm. Various methods for distance estimations are using: Received Signal Strength Indicator (RSSI), Angle of Arrival (AoA), Time of Arrival (ToA) and Time Difference of Arrival (TDoA). All these methods form the core of Range-Based techniques and will be discussed in next section.

Once the distance between nodes in its neighbours has been found, the next step is position estimation using those estimated distances [4]. The three main approaches for this step are:

A) Triangulation

Most of the localization algorithms use this technique. It simply involves collection of Angle of Arrival (AoA) data from three or more neighbours or sources, typically anchors/landmarks. Using those AoA measurements and geometric properties of a triangle, the position of an unknown node is estimated.

B) Trilateration

It involves collecting tuples from sources in form (m,n,d), here (m,n) is the location of the anchor or also called reference and 'd' is the distance between anchor and sensing node. A minimum of three sources or anchors are required in this approach. The estimated position of unknown sensing node's' is point of intersection of three circles in 2D plane.

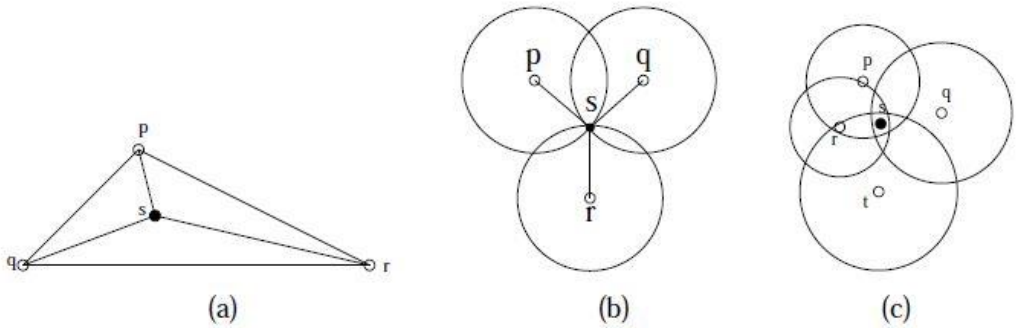

Figure 5: a) Triangulation b) Trilateration c) Multilateration

C) Multilateration

This technique tends to minimize the sum of squared distance between an assumed sensor locations and anchors. To compute the location of a sensor node S following formula can be used:

$$min \sum (dist_{s,i} - \widehat{dist}_{s,i})^2 \tag{1}$$

$$dist_{s,i} = \sqrt{(X - X_i)^2 + (Y - Y_i)^2} \tag{2}$$

1.2.3 Classification of Localization Techniques

Localization algorithms can be subdivided into three broad categories:

1. Centralized and distributed algorithms
2. Anchor based and anchor free algorithms
3. Range based and range free algorithms

Centralized algorithms require various estimations and calculations to be done on a central node or station. Each sensing node collects information of measurement and sends them to a central machine for calculating the position of that sensing unknown node. The main advantage of this approach is that it requires less hardware and computation support on behalf of individual nodes. But this comes at the cost of making the central station expensive and putting the risk that whole localization process becomes futile when that central station fails. In contrast, Distributed algorithms require computation to be done on each sensing node. Each node itself is responsible for computing its coordinate estimates using measurements received from anchors or landmarks. It makes the sensor network more robust and fault tolerant. Furthermore the cost is equally divided over all the nodes. Some of the distributed localization algorithms are discussed in subsequent sections.

Another class of localization algorithms, Anchor based algorithms require anchors or landmarks for determining the positions of unknown sensor nodes. Most of the localization algorithms fall into this category. Conversely, anchor free localization algorithms do not require any landmarks or other such nodes whose location is pre-known. But this class of algorithms require more complex computation. Some of the anchor free algorithms are: Spotlight Localization [5] system which estimates the position by exploiting some space-time properties when an event is generated and time when this event is perceived. Another such algorithm is Light House [6] algorithm. This technique uses a device known as lighthouse and finds out the distance between light house and sensor node.

1.3 Range Based Localization Schemes

Range based techniques rely on node to node distance, angle measurement, and relative speed measurement for time computation. Once we have achieved the result of ranging, positions can be computed using either of triangulation, trilateration or multilateration techniques. We will discuss three main ranging methods: RSSI, AoA and ToA.

1.3.1 Received Signal Strength Indicator (RSSI)

The energy of the transmitted signal decreases as the distance between the transmitter and receiver node increases. The attenuation is in polynomial terms that is proportional to square of distance [7]. So based on the received signal strength the distance can be measured using the following formula:

$$RSSI\ [dBm] = RSSI_{src} - 10 * n * log_{10}\left(\frac{dist}{dist_{src}}\right) \qquad (3)$$

RSSI has been measured in dBm. $RSSI_{src}$ is the signal strength value at source. n is a computational constant having value between 3 and 6.

If we use $dist_{src}$ as 1 meter, the equation 3 becomes:

$$dist = 10^{\frac{RSSI_{src} - RSSI}{10n}} \qquad (4)$$

1.3.2 Angle of Arrival

To achieve localization using AoA data, two angle measurements are needed. A good demonstration is being presented in [8] and can be visualized from following Figure 6:

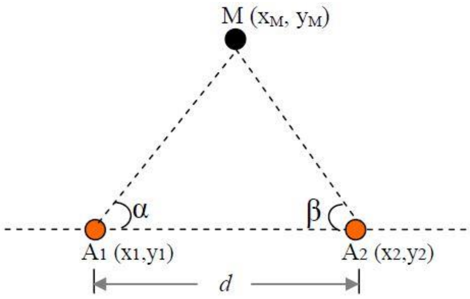

Figure 6: Angle of Arrival Measure [8]

Each of the anchors A1 and A2 have antenna arrays which receive the signal from M at angles shown in diagram. Finally M can compute its position coordinate using following formula:

$$X_M = X_1 + \frac{d*sin(\alpha)\, sin(\beta)}{sin(\alpha+\beta)} \quad (5)$$

$$Y_M = \frac{d*cos(\alpha)\, sin(\beta)}{sin(\alpha+\beta)} \quad (6)$$

1.3.3 Time of Arrival (ToA)

For ranging using Time of Arrival, time taken for the signal to propagate from transmitter to receiver is measured. It requires the sender and receiver to be synchronous and thus needing extra hardware support for maintaining synchrony [9] [10].

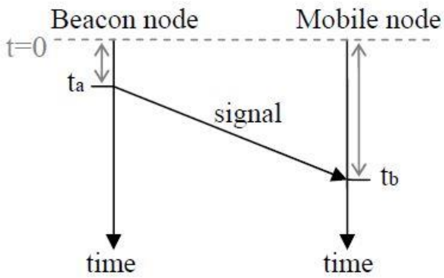

Figure 7: Time of Arrival Measure [8]

Table 1 describes the tabular comparison of various range free techniques. RSSI is the simplest amongst all three as it requires no additional hardware and is easily scalable. But this comes at the expense of low accuracy. AoA has better accuracy but it requires antenna arrays and has hardware limitations. ToA has high accuracy but it involves stringent computations.

Table 1: Range based techniques

Ranging Method	Measurement metrics	Benefits	Shortcomings
RSSI	Signal strength	✓ No additional hardware need ✓ Inexpensive ✓ Synchronization not required ✓ Scalable ✓ Low Overhead	✓ Low accuracy ✓ Non flexible ✓ Susceptible to noise and attenuation ✓ Memory cost
Angle of Arrival	Angle subtended by anchor on Node	✓ Minimum time synchronization needed ✓ Better accuracy than RSSI ✓ Only at least two anchors needed	✓ Hardware constraints ✓ Need antenna arrays ✓ Erroneous measurement due to diffraction
Time of Arrival	Time to perceive signal	✓ High accuracy ✓ Low overhead ✓ No synchronization at source	✓ Rigid computations ✓ LOS need to be assumed

1.4 Range Free Localization Schemes

Range free localization algorithms tend to exploit the available connectivity information and avoid explicit use of ranging. The connectivity information is in form of number of hops between any two sensing nodes. This hop count reflects how close or far the sensing nodes are. If two sensor nodes are directly within the communication range of each another, they will be called adjacent to each other and the hop count will be one. Most of the range free localization schemes use location-aware nodes called as anchors or landmarks. Typically the anchors are static and nodes may be static and mobile. But recently, several algorithms have been proposed which deal with mobile anchors too. This section discusses the primitive range free techniques proposed over the years: Centroid [11], Approximate Point in Triangulation (APIT) [12] algorithm, DV hop algorithm [13], CPE algorithm.

1.4.1 Centroid Algorithm

This is the most basic and simple approach to localization. It involves n anchor nodes with overlapping areas being deployed in a particular region. Each of the landmarks A will broadcast their location. Each sensing node N receives beacon from anchors and calculated "Connectivity Metrics" by following formula:

$$ConMetric_{(K,A_i)} = \frac{N_{recvd}(A_i,t)}{N_{send}(A_i,t)} \tag{7}$$

The estimated position can be computed as:

$$(X_M, Y_M) = \left(\frac{X_{A_{i1}}+\cdots+X_{A_{ik}}}{k}, \frac{Y_{A_{i1}}+\cdots+Y_{A_{ik}}}{k}\right) \tag{8}$$

Where k is the number of anchors with connectivity greater than set threshold. A variant [14] of Centroid algorithm is weighted centroid algorithm. In this approach, the author assigned a weight to the path from anchor to sensor node. With this experiment, the author was able to confine the RSSI range from -110dB to -50dB. The achieved results were better than Centroid and position moved closed to landmarks with increase in weight.

1.4.2 A Point in Triangulation

APIT performs location estimation by recursively partitioning the deployment region in triangular areas. With the selective combination of three anchors A, B, C, the node M determines whether it is outside or inside the triangle formed by these anchors. The process is repeated with all possible 3 anchors. Then the node computes the centroid of all triangles in which it resides as its estimated position.

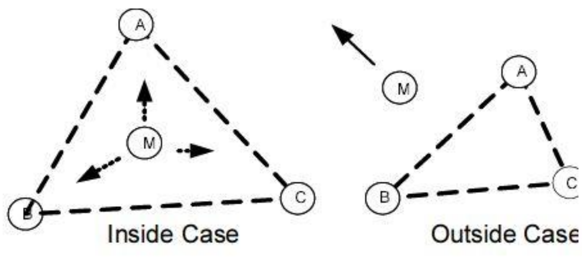

Figure 8: APIT Localization

[15] Proposes an improvised APIT approach with the use of virtual nodes. APIT has uneven deployment of nodes. VN-APIT deploys the nodes “rationally” to determine whether a node is inside or outside the triangle of selected anchors. Therefore it is independent of density of nodes and their distribution pattern. The localization accuracy is somewhat similar.

1.4.3 DV Hop Localization

This approach eliminates the need of having at least three anchors to successfully localize a node. This come in handy in topologies where it’s not possible for some nodes to be surrounded by three neighbors or anchors. In the first step node determines how hops away it is from each anchor and next the each anchor computes how much far it is from every other anchor and then calculates the average hop size as mentioned in equation below. In this, once the node is aware of number of hops to anchors it calculates an average size of each hop by following formula:

$$Hsize_i = \frac{\sum_{k\neq i}\sqrt{(X_i-X_k)^2+(Y_i-Y_k)^2}}{\sum_{k\neq i} n_{ik}} \tag{9}$$

Here, (Xi, Yi) and (Xk, Yk) are positions of anchors i and k, nik is the number of hops between these two. Then, the distance from unknown sensing node to anchor can be computed as:

$$dist_i = Hsize_i * N_i \tag{10}$$

Here, N_i is the hop count between node and anchor and $Hsize_i$ has already been computed in equation (9).

1.4.4 Convex Positioning Estimation

CPE algorithm [16] solves the problem of localization by framing it into an optimization MAX-MIN problem. The objective of this approach is to find out the smallest rectangle that bounds the overlapping radio of three anchors and then computes the center of this rectangle as the estimated position of node N_x. This algorithm is essentially implemented in centralized manner due to the fact each of the sensing node might not be able to do the complex computations because of the resource limitations. The most tedious step in this algorithm is to find the smallest bounding rectangle.

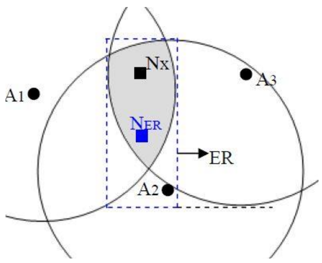

Figure 9: CPE Localization

[8] Provides a wonderful demonstration of the approach to find the smallest rectangle. Suppose A_1, A_2, A_3 be three anchors. N_{ER} is the estimated position of node.

Table 2 shows a tabular comparison of primitive range free localization techniques. Centroid scheme has the least localization accuracy followed by APIT. VN-APIT demonstrated enhancements over APIT in terms of power consumption but the accuracy was similar to APIT. DV hop had better accuracy than APIT and eliminated the need of having at least three anchors to localize an unknown sensor node. CPE had the best accuracy of all but was somewhat complex and incurred more overhead.

Table 2: Range free techniques

Algorithm	Type	Advantages	Shortcomings
Centroid	Decentralized	✓ Low overhead ✓ Simple computations ✓ Scalable	✓ Low accuracy ✓ Nodes must be static ✓ At least 3 anchors required
APIT	Decentralized	✓ No ideal assumptions required ✓ Simple computations	✓ RSSI required ✓ High power consumption ✓ Low accuracy
VN-APIT	Decentralized	✓ Independent of node deployment ✓ More rational and logical than APIT	✓ Better or equal accuracy than APIT ✓ Less computations than APIT

DV Hop	Decentralized	✓ Localization even with two anchors ✓ Better accuracy than APIT ✓ Provides connectivity information of nodes	✓ More overhead ✓ Less scalable ✓ Mobility makes complexity large ✓ More memory requirement
CPE	Centralized	✓ Higher accuracy	✓ Single point of failure ✓ High overhead

1.5 Organization of Thesis

Organization of the rest of the thesis is in following manner: Chapter 2 contains an extensive review of the literature that have been studied for the formulation of the problem statement. Chapter 3 contains the scope of the study. Chapter 4 contains the problem statement and objectives of the thesis. Chapter 5 discusses the extensive research methodology along with required preliminaries and network model. Chapter 6 contains the results of the simulation followed by Chapter 7 concluding the study and putting forward the future research directions.

CHAPTER 2

REVIEW OF LITERATURE

This chapter presents a comprehensive survey of numerous localization techniques studied before the problem statement formulation. For the sake of convenience, the techniques have been classified section wise.

2.1 Localization Using Antennas

SeRLoc: Secure Range-Independent Localization for Wireless Sensor Networks [17] was the first ever secured range free position estimation scheme. In this study, the authors proposed a secured localization method immune to attacks such as black hole, wormhole, Sybil attack and malicious selfish nodes. The study assumes that all nodes are equipped with directional sectorial antennas. The first step is the position estimation in which each node computes its position as the center of gravity of the overlapping sectors from which they receive beacons. To incorporate the security feature, all beacon messages from anchors were encrypted using symmetric key scheme 64-RC5 via a global secret key. The IDs of the anchors were authenticated using hash functions such as MD5. Attacks such as wormhole attack were detected using various properties- unique sector characteristics, range violation characteristics.

HiRLoc [18] was developed by the same authors in same year as an attempt to minimize the region of consideration for location estimation. The authors proposed a Higher Resolution robust localization algorithm called HiRLoc. The algorithm minimizes the overlapping area by tweaking the transmission power and by the use of directional antennas. The scheme obtained the position information of an unknown sensor node by computing the centroid of the overlapping area, in which the anchor’s beacon signal contains the position of anchor along with various other control information, the angle of broadcasting range of directional sectorial antenna and radio communication range R. The algorithm did not rely up on the deployment pattern of anchors. Simulation of this approach showed that when the effective number of beacons is 15, the localization error reaches up to 0.2R.

C.W Fan et.al in [19] proposed a Signal strength based Geometric localization called RGL. It uses mobile landmarks (ML) equipped with omnidirectional antennas, the sensor node are fixed. The ML moves throughout the sensor network periodically broadcasting beacons. Each beacon contains ML locations and RSSI value. The unknown sensor node receives a sequence of such beacons whenever it comes within the range of ML. the unknown sensors use maximum Signal strength value and its corresponding location information to localize itself. The study does take into consideration regarding the energy consumption by the nodes in the network.

However, omnidirectional antennas have various shortcomings in comparison to directional antennas. They are more prone to interference and in contrast, the directional antennas have high beam gain and thus larger transmissions range and coverage. Thus as a consequence, they can lead to less localization error and greater accuracy.

Another similar algorithm, albeit a better one based upon antenna is studied in [20] which proposes a directional antenna dependent localization scheme called **DIR**ectional algorithm (DIR). It uses 8 mobile landmarks (ML) each having 4 directional antennas: 2 aligned parallel to X axis and 2 aligned parallel to Y axis. A compass is needed to make sure that alignment is intact even during the motion of landmark. Experimental studies suggested that the mean energy for receiving the beacons was in range of 1.31mJ to 13.47 mJ as the beam angle varied from 5 degrees to 50 degrees. Similarly, the mean energy for transmitting varied in range of 12.9 mJ to 13.5 mJ with variation in beam angle

An improvisation on the above two approaches was proposed in [21] in which the authors postulated a combined Range based and Directional Antenna equipped Mobile beacon approach called **BRM technique**. It works for the randomly distributed static nodes which are localized using a single mobile beacon node (BN). The BN moved along a certain path and broadcasted beacon signal message at fixed specified points along the movement. In this study the authors specify the beacon packet transmission every BW/2 distance where

$BW = 2 * Range_{max} * \tan(\alpha/2)$ and α is beam angle.

The X coordinate of the unknown node is computed by the power of the received signal using the following formula:

$$d_{i,j} = d_0 \left(\frac{P_{ij}}{P_0(d_0)}\right)^{-1/n_p} \qquad (11)$$

And the Y coordinate is simply the Y coordinate of the BN at the point when unknown node received the beacon packet. Simulation results showed that with increase in beam angle from 5 to 50 degrees the average localized error reduced by nearly 66.37%, average energy consumption was reduced by 91.54% and localization coverage was improved by 18.64% compared to DIR technique.

2.2 Localization Using Fuzzy Logic

The work in [22] proposed a probability based fuzzy system in which the authors modeled the localization problem using a probabilistic fuzzy logic approach. It uses if else based fuzzy rules which took RSSI as input and gave Weight as output. The output weight was fed to weighted centroid method to compute the estimated position. Wight reflects the proximity of anchor to the unknown sensor node. The authors used Mamdani Fuzzy inference system. Each of the rule was associated with an output probability vector V. For example, a rule can be defined as

"*IF RSSI is high then Weight is medium with a probability of 0.1 and weight is high with a probability of 0.8 and weight is very high with probability 0.1.*"

The authors used one input, five rules and one output fuzzy system. The input has five membership functions namely: very low, low, medium, high, and very high. Therefore the output probability vector for the above rule can be written as

$$V= [0.0 \;\; 0.0 \;\; 0.1 \;\; 0.8 \;\; 0.1]$$

Simulations result showed that average localization error for traditional fuzzy based localization system was 2.27m whereas in case of probabilistic fuzzy approach it was 1.99m. The latter was more effective in noisy environment and the results were very promising.

In the study done in [23] by **Ashok Kumar et al**., the authors use weighted centroid algorithm by calculating the weights as an output variable from the fuzzy inference system. The FIS takes RSSI as input variable and its range was [0 $RSSI_{max}$] and the range of output variable was between [0 1]. Five membership functions were defined for each of the input and output variable. The authors study the results of four techniques Sugeno based, Mamdani based, combined Sugeno-Mamdani and ANFIS Sugeno. Combined Sugeno-Mamdani averaged the weights obtained from Sugeno and Mamdani individually. ANFIS was used to refine the membership functions *params* using back propagation method or a hybrid method of back propagation and least square methods. For a simulation environment of 60 unknown sensors and 121 anchors in non-cooperative localization, the average localization error for simple centroid was 1.61m, for Mamdani FIS was 0.8956m, for Sugeno was 0.95m and for combined Sugeno- Mamdani was 0.76m. The authors also simulated a cooperative localization using 25 anchors, 60 unknown sensors. In this scenario the average error for combined Sugeno-Mamdani was 1.74m.

The work done by **Arbabi Monfared** in his Master's thesis [24], the author explicitly used Sugeno based fuzzy logic to compute the weights which were fed to the weighted centroid algorithm. The fuzzy system used in this study comprised of one input variable: RSSI (logarithm value was taken) with range [-80, 0], one output variable: weight with range [0, 1] and nine if-then rules. Each of the variable has 9 membership functions namely: very very low, very low, low, medium low, medium, medium high, high, very high and very very high. Simulation results of with and without AWGN (Additive White Gaussian Noise with SNR of 10) were studied. The average error for Sugeno FIS without AWGN was 0.26m and that with AWGN was 0.30. The authors also replicated the results in experimental study to obtain an average error of 0.53m. The RSSI vs weight surface obtained form FIS was similar to following figure:

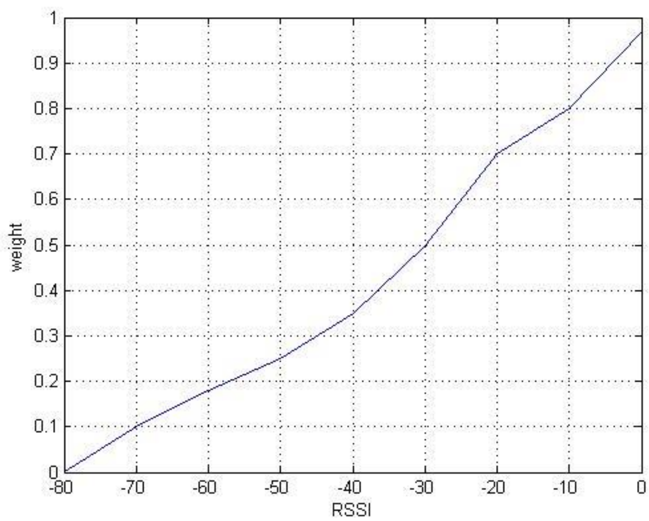

Figure 10: Weight vs RSSI Graph [24]

Ashok Kumar et al further improvised their previous work on fuzzy logic based localization in [25]. The authors studied a fuzzy logic based weighted centroid scheme in which weight was calculated based on RSSI and Link Quality Indicator (LQI) as input variables. In the first step, unknown sensor finds out the number of anchors it can listen to, based upon the number of beacons received. Next it computes the edge weights using RSSI and LQI where

$$LQI = \frac{255*(N_{tran} - N_{recvd})}{N_{tran}}, \quad 0<LQI<255 \tag{12}$$

N_{tran} is the number of bits sent by anchor and N_{recvd} is the number of bits received by unknown sensor with error. The input variables RSSI and LQI each had 3 membership functions: low medium and High, while the output variable edge weight had five membership functions namely: very low, low, medium, high and very high. Total 9 if-then rules were defined. Simulation results showed that in a scenario considering AWGN along with external noise radio frequencies of -30dBm, the mean localization error for Mamdani FIS was 0.89m, for Sugeno FIS was 0.971m and for combined Sugeno-Mamdani was0.781m.

Indhumathi and Venketasen in [26] propose a deployment model for dynamically deployed nodes to obtain maximum coverage distance using genetic algorithm. Authors used GA to select some best sensor nodes that can be initially deployed in the sensing field. Then in the next step any uncovered or undeployed area is identified. Node distance is the radio range or the coverage of the node. Genetic algorithm involves five steps: Initialization, Selection, Crossover, Mutation and Termination. In the initialization phase, nodes were deployed randomly with each node being represented by 20 bits string gene. Next, the fitness function selects the best nodes using tightness ratio. In the selection phase, tournament procedure is used. Among the two nodes available, the one having the best fitness value is chosen. Then in the crossover phase, gene bit strings are crossed over as the following example:

110010000111000|11010 → 11001000011100011100

100110001100011|11100 → 10011000110001111010

In the mutation phase, a random number was generated and if it was greater than the mutation probability of 0.01, the bit 0 was flipped to 1 and bit 1 to 0 as shown in following example:

11001111000000110011 → 11001111000000110111

Simulation results of 150 total nodes and 100 deployed nodes in a sensing area of 100*100 m showed that uncovered area was reduced after the cluster gap was reduced.

In the work done by **Gharghan et al**. in [27], the authors used Adaptive Neuro Fuzzy Inference System (ANFIS) in which the input was three distinct RSSI values obtained from 3 distinct anchors. For each input, 3, 5 and 7 membership functions (*mf*) were trained. The authors studied and compared the results of two difference kinds of $mf_{s:}$ *trimf* (triangular *mf*) and *gbellmf* (bell shaped *mf*). Very large samples consisting of 900 RSSI values were used, out of which 70% was used to train the ANFIS, 15% was used to test the ANFIS and remaining 15% was used to validate the ANFIS. The authors studied the result of both indoor and outdoor environment and conclusively found that results of indoor scenario was less accurate and promising because of phenomena such as multipath scattering. The Mean Absolute Error and Root Mean Square Error for indoor scenario was less accurate than that of outdoor scenario for all the three cases. Furthermore the results of *gbellmf* was more promising than that of *trimf*. Also both MAE and RMSE decreased with increase in number of membership functions from three to five and eventually to 7 *mf*.

2.3 Localization Using Machine Learning

Morelande et al. in [28] studied application of machine learning methods in sensor networks and proposed a localization technique based on Bayesian probability. Two different kinds of probabilities were used: prior and posterior. Prior probability denotes the probability of a hypothesis when evidence has been observed. The idea was to predict samples that best fit the posterior probabilities or likelihood. This scheme uses very few anchors and worked efficiently for large scale sensor networks where number of deployed nodes are in range of thousands. The algorithm was implemented in centralized mode and was moderately complex.

In the study done by **Yang et al**. in [29], the authors studied the application of Support Vector Machines (SVM) classifiers to solve the localization problem in wireless sensor networks. A mobility based approach was used in which the movement was tracked by Received Signal Strength Indicator or RF oscillations. A change in value of RSSI denoted that the node has moved to some other location. Large training sets of RSSI were fed to SVM to output the new estimated location. The simulation results showed that the processing time was significantly reduced and so was the computational complexity but, the method was very sensitive to any outliers, incomplete or missing values in the training data set. The technique was less hardware intensive and thus was implemented in distributed manner.

Gu and Hu in [30] attempted to use Gaussian processes to model sensor networks.In this study, the sensors were deployed in the monitoring region through Gaussian distribution process. The mobility was modeled using Distributed Gaussian Process Regression (DGPR) which predicted optimal positions for node movement. Each node implemented the Gaussian Regression locally and independently using collected information from local anchors. Conventional GPR has a complexity of O (N^3), N= sample size, whereas the proposed techniques had a computational complexity significantly low.

2.4 Localization Using Neural Networks

Zheng and Dehghani in [31] propose a novel range free connectivity based localization algorithm using Neural Networks i.e.LNNE (Localization using Neural Network Ensembles). The study assumes that there are multiple anchors in the network and unknown sensors node communicate with them directly or indirectly. Every node has fixed radio range R. Further, the authors have used two network ensembles separately for computing X and Y coordinate. Each of the X and Y NNE comprises of 'C' components where, each component represents a 3- tiered feed forward model. The anchor nodes, A_j are logically placed in input layer. The unknown nodes U_i are placed in hidden layer. The input to the NNE is the hop count that is the number of hops and unknown node is away from the anchor. So the input is expresses as $h(U_i, A_j)$. The output from each component is the estimated 'x' coordinate from that particular component $x_{estUi,c}$. To find the estimated location, the authors have used mean.

$$X_{est_{Ui}} = \frac{1}{C} \sum_{i=1}^{C} x_{estUi,c} \qquad (13)$$

Similar methodology has been used for find the estimated Y coordinate. The authors have also proposed and optimization algorithm for refinement called EMSO ("Enhanced Mass Spring Optimization"). It consists of a cooperative approach, where position data of anchors and unknown nodes are taken into utilization. The authors compared the results vis-a-vis traditional range free approaches: Centroid and DV Hop. The localization accuracy was improved by a factor of 21% approximately. The mean localization error in LNNE with 30 anchors was 2.78m and that with 70 anchors was 2m.

Shiu Kumar et al in [32] studied the application of neural network techniques in sensor node localization. In this study, the authors proposed a neural network based localization relying on feed forward model. The authors studied the impact of different anchor ratios and their configuration on localization accuracy. The received Signal Strength Indicator (RSSI) from three anchors comprised the input. The hidden layer was modeled as 12-12-2 structure. The first two layers in the hidden layer used Sigmoid functions as activation function and the third sublayer used "*purelin*" activation function. The output layer had two nodes: one each for the computation of x and y coordinate of unknown node. The authors studies the effect of multiple training models: LM ("Levenberg- Marquardth") and BR ("Bayesian Regularization") and concluded that average localization error in BR was less than that of LM training model. Each of the training model used multi-layer perceptron. The results were further validated in real world scenario using 802.15.4 ZigBee sensors and microcontrollers. The average localization error was 0.295m.

2.5 Localization Using Particle Swarm Optimization

In the work done by **Satvir Singh et al**. in [33], the authors propose a distributed, cooperative localization scheme based upon Biogeographic Based Optimization (BBO) and PSO. The impact of multiple variants of BBO namely Blended BBO (BBBO), Enhanced BBO (EBBO) on localization accuracy has also been studied. BBO is a method that emulates the distribution pattern of plants and organism species over the time and space taking into account their migration behavior. It is an optimization technique similar to ACO, GA and Simulated Annealing. The localization methodology is as follows: Some target nodes and anchors were randomly deployed in the deployment region. Each unknown node needed a minimum three anchors to be successfully localized. Initially, the mean of position of anchors in the radio range of unknown node was considered to be estimated position. In the next step, each node runs PSO, BBO, EBBO and BBBO. A fitness function in form of least square problem was formed which represented the error between the measured distance and estimated distance, (here measured distance refers to distance computed using BBO, EBBO, BBBO and PSO). Simulation results showed that the average localization error for BBBO was less than that of PSO, BBO and EBBO but at the expense of more computational complexity.

Monica and Ferrari further studied the swarm optimization techniques in [34]. This study proposes a cooperative localization scheme using computational intelligence technique known as Particle Swarm Optimization (PSO). Sensor nodes in the deployment area communicated with each other using UWB (Ultra Wide Band) signaling. The location estimation has been done by considering Two Stage MLE (Maximum Likelihood Estimation) as an optimization problem to be solved by PSO technique. The algorithm starts with four anchors and for each iteration nodes whose position have been computed becomes anchor in next iteration. The PSO technique has been used in following manner: the candidate solutions of the optimization problem framed as least square problem can be considered as a swarm of size M. Every particle in the swarm has, at any moment 'n', a position associated with it say $x^j(n)$, for all j= 1,2,…….,M.

Every member of the swarm knows at each step the best position of self (*pbest*) and its neighbor members (*gbest*). In the next iteration, they use this information to estimate their best position. Simulation results showed that Mean Square Error (MSE) of PSO was several factors less than that of TSMLE without PSO.

2.6 Mobile Localization Schemes

In the study by **Baggio and Langendoen** in [35], the authors proposed two different schemes called Monte Carlo Localization and Monte Carlo Boxed Localization based on probability distribution. This algorithm extended the application of MCL used in field of robotics to track the movement of robots. The algorithm comprises of 2 principal phases: prediction phase and filtration phase. In the prediction phase, an unknown sensor node envisages its assessed position using distributed switching equipment utilizing the mobility information of the mobile anchor. In the filtration phase, that unknown node removed any unreliable information from the computed position information. MCL can provide accurate position of nodes even with low anchor density and extremely irregular deployment conditions. In cases, when an unknown node cannot localize itself in first pass, the algorithm needs to be run in multiple passes. After the prediction stage, when we have collected samples and filtration of sampling fails the, MCL can create infinite loop filtering the samples. The author run simulations to show that the algorithm relies vastly on the posterior probability distribution utilizing discrete sampling. Hence, more the number of samples, better the localization accuracy, but this comes at the cost of more memory requirement and computational overhead.

Alaybeyoglu improved the efficiency of MCL proposed in previous literature in [36]. This study proposes an improvement over MCL scheme with no constraint on density and distribution pattern of nodes. It also presents a Sequential Monte Carlo Localization Algorithm (SMCLA). SMCL has two phases: Prediction phase and Update phase. In the prediction phase, a circular area is considered around the position obtained in the previous iteration and nodes are distributed around the position as center of circle. In the next phase, the irregularity of radio model is taken into consideration by identifying the nodes who have left the circular region and nodes who have been freshly added to the circular region. To model the mobility, different models namely: Constant Velocity (CV), Constant Velocity Circular Turn (CVCT) and Constant Acceleration (CA) were used. To simulate the algorithm, the author has used network simulator tool NS-2 with a sample of 300 nodes, out of which 25 nodes are anchors/landmarks and rest 275 nodes were unknown nodes whose position was to be computed. Simulation results showed that the localization accuracy of SMCLA was best as compared to centroid, DV hop, MCL and amorphous algorithm. But a critical analysis suggests that a certain trade-off between accuracy and computation time exists. The SMCLA took the maximum computational time vis-s-vis the other algorithms mentioned. The additional time stems from the fact that SMCLA implements multiple iterations for regular updates of the node in the update phase. Also, the best performance of SMCLA is due to the reason that in successive iterations nodes are placed closer to the position obtained in the previous iteration.

Liu Y in his Master's thesis [37] proposed a Distributed Mobile Location estimation algorithm for deployment consisting of static anchors/landmarks and mobile sensor nodes. This algorithm epitomizes the idea of using the mobility to achieve localization. Under this, each unknown sensor node maintained a queue which is populated with three most recent locations, and based on that we can construct an equation of the linear motion an unknown node exploiting the history queue records. We can make an assumption that the sensing node whose position is to be determined is in linear motion in multiple short time intervals and with constant acceleration. Results showed that, the localization coverage of this algorithm can be achieved as high as 99% with correct choice of radio range. When the ranging error increased up to 40 percent, the localized mean square error of the algorithm was only 33 percent and that of any conventional localization approach reached up to 50%.

The work in [38] by **Haldar and Ghosal** presented a broad and comprehensive review on various mobile node localization techniques with either anchor being static or sensors or both. The authors identified the key design issues of problem of mobile node localization such as accuracy/precision, absolute and relative position, hardware requirement, cost incurred in scaling the algorithm to large scale sensor networks. The main challenges as studied by the authors are: path of movement of anchors or anchor trajectory; node density (if number of anchors is large, accuracy would be better); noisy media (need to compensate for signal strength loss) etc. This study also reviewed various path planning schemes for modelling the mobility of anchors such as RWP model, Gauss Markov model and dynamic path planning models such as CIRCLE, HILBERT etc. A detailed study of Gauss Markov model has been presented in **Appendix A**.

Hao Y in [39] promulgated a distributed target tracking localization approach based on energy source. It is a cluster based algorithm. It divides the sensor network into multiple non overlapping clusters and each cluster has an anchor associated with it which has the responsibility of discovering the target, assignment of task, and establishment of a smooth communication channel between two clusters. The algorithm best works with mobility scenario. When any unknown node migrates to a new cluster, the cluster head which is an anchor estimates the position of that unknown node and so on. At last the location of the unknown node is determined by mutual cooperation of all clusters. The algorithm computes the distance between anchor and an unknown node and then employs trilateration. This technique significantly minimizes the computational overhead and complexity.

Neuwinger et al. in [40] attempted to exploit the self-organizing tendency of wireless sensor networks. In this work, the authors proposed a time based location estimation scheme for mobile sensors and mobile anchors. This type of localization technique rely on the self-organization property of wireless sensor networks. This algorithm assume that mobility of sensor nodes is in continuous fashion, so the location coordinates of unknown sensors would not have changed much. The computation of coordinates of unknown node was done using trilateration. Simulation results showed that average localization error was 2.5 meters when distance between anchor and unknown sensor was 30 meters. A critical analysis of algorithm suggested that for better efficiency of this algorithm the anchors need to move at slowest speed possible.

2.7 Connectivity Based Schemes

Chen and Xhang in their work in [41] studied an improvised DV hop localization algorithm. It is an improvisation of traditional DV-Hop localization algorithm. The traditional DV-Hop algorithm uses adjacent anchor node's metrics such as average hop distance which has perils of large computation errors. In this improvement, the authors used the mean hop distance from all the anchor nodes in n-hop range of a sensor node. After the position coordinates of sensor nodes are obtained, the location of anchor node is estimated again to compute the correction factor. This correction factor is broadcasted to all unknown nodes. All the correction factors from anchors is weighed and average correction factor is used for location correction of unknown nodes. Similar to the conventional variant of DV-hop algorithm, the improved version of algorithm also shows improved accuracy with improved node density.

Kumar, M kumar and Sheeba studied how efficiently the localization of sensor nodes can be done in irregular deployments in [42]. In this work, the authors propose a novel range free localization scheme that works efficiently in presence of hurdles or obstacles. The proposed model assumed that nodes were deployed randomly and the anchor nodes are mobile. The radio communication pattern was also irregular with obstruction being also random and uncertain. The input was hop count broadcasted by mobile anchors to all unknowns in its radio range. The performance of the proposed algorithm was compared vis-à-vis other range free techniques APIT and DV hop. Simulation results showed that the Average Localization Error (ALE) decreased with increase in anchor density. The decay pattern is first linear, then exponential and then again linear. Also with the increase in radio range from 2 to 3m, the ALE decreases progressively yet linearly. With increase in radio range from 3 to 6m, the decrease is less progressive with somewhat constant in the end when radio range becomes 8m. An analysis of results also showed that the average localization error was least, as low as nearly 5%, compared to APIT and DV hop. The ALE was worst for the APIT scheme.

Y Liu in his study in [43] proposed an amorphous localization scheme in the lines of other connectivity based schemes such as DV hop, relying completely on hop count information and not the Euclidean distance values. In the first step, each unknown host computes the minimal hop count to the anchor it received beacon from. Each anchor periodically broadcast beacons which are heard by every other node in its radio range. In the next step, the unknown computes distance to the unknown node using

$$distance = hzize_i * hc(i,j) \tag{14}$$

hc(i,j) is the minimal hop count from unknown node 'i' to an anchor 'j'. Once the distance d_i to n anchors have been computed the location of unknown node can be found out using multilateration. Simulations performed by **R. Khadim et al. in 2015** showed that the mean square error for amorphous algorithm was 0.2361 m, better than both centroid and DV hop.

Poonam Pabla et al. in [44] reviewed the existing connectivity based localization techniques. The authors subdivided any localization technique into two principal stages: First, ranging process in which sensor nodes assess their Euclidean distance or angle from anchors; and second, in which unknown sensor noes use that estimation to compute their positions. The authors considered various localization parameters such as accuracy, precision, scalability, self-organization (ability to form/deform without any external aide), power consumption, node density, mobility etc. The study concluded that range free techniques provides coarser estimations. Distributed algorithms, although having large mean localization errors, are easily scalable. Anchor based approaches have high accuracy, large power usage, medium communication cost, medium robustness but are difficult to maintain as compared to anchor free approaches.

CHAPTER 3

SCOPE OF THE STUDY

This study presents a novel range free localization scheme based on Sugeno-Mamdani fuzzy inference systems. Localization being a nondeterministic and uncertain can effectively be solved by soft computing techniques such as fuzzy logic. A coverage of almost 100% can be achieved in least computational time. The average processing time of the proposed technique was approximately 2.5s. The number of anchors required to localize the nodes is also extremely less. Furthermore, being computationally simple, the algorithm does not require any extra hardware and can be implemented in pure decentralized manner. This study also offers new insights into how optimization techniques such as Gauss Newton method can be used to significantly improve the localization accuracy and to solve the problem of localization in large scale sensor networks where number of sensor nodes are in range of thousands.

CHAPTER 4

OBJECTIVES OF THE STUDY

With the inherent limitations of sensor networks such as low energy reserves, minimal computational and communication ability, limited storage facility, it is virtually impossible to deploy GPS on each sensor node for position information. Further, the range based approaches are more susceptible to computational errors. Thus the emphasis must be shifted towards range free techniques. The principal objective of this study is to design an appropriate network scenario for a range free localization algorithm relying on Fuzzy Inference Systems (FIS) and figure out an analysis of various parameters and factors that constitute for an effective localization scheme.

4.1 Problem Statement

Given N number of sensor nodes deployed in a particular 2-D area, how can we use fuzzy logic systems as a primitive to Gauss Newton Optimization to find the position coordinates (x_i, y_i), for i=1,2,3,……,N with the help of only four anchors deployed at four corners of the deployment area? Furthermore, are the results promising and acceptable vis-à-vis parameters such as cost, accuracy, coverage, running time complexity?

4.2 Objectives of Thesis

The objectives of this study are:

- To design a joint Sugeno-Mamdani type fuzzy inference system for computing the weight corresponding to a RSSI value
- To decide the parameters of interest for determining the effectiveness of designed scheme
- To analyze the impact of Gauss Newton optimization method on localization accuracy of proposed scheme
- To compare the effectiveness of proposed scheme with existing fuzzy based localization schemes

CHAPTER 5

RESEARCH METHODOLOGY

5.1 Assumptions and Parameters of Interest

1. All the sensor nodes, except the anchors, were deployed randomly.
2. There is Line of Sight (LoS) communication.
3. The anchors are placed on the corner of deployment area.
4. There is no attenuation in signal strength while in transit.
5. There is no collision among two or more signals.
6. The deployment region has no irregularities or obstacles.

The various factors for consideration and comparison are:

1. **Localization coverage**: It refers the percentage or ratio of nodes correctly localized. This study assumes that the nodes whose estimated position lie outside the deployment region are considered to be non-localized.
2. **Localization error**: The mean absolute error will be computed as:

   Suppose (x_{cen}, y_{cen}) is the computed position of a node and (x_i, y_i) is the actual position of the node then the mean absolute error can be calculated as

   $$\sum_{i=1}^{n} \frac{\sqrt{(x_{cen} - x_i)^2 + (y_{cen} - y_i)^2}}{n}$$

   Where n is the total number of nodes deployed.
3. **Cost trade off**: We should look for a localization algorithm which uses less number of anchors. More the number of anchors, more the cost burden. Furthermore increasing the number of anchors does not necessarily guarantee better localization coverage or accuracy. So we need to maintain an optimal anchor to nodes ratio. Cost will also depend on power equation.
4. **Algorithmic complexity**: The space and time complexity of centralized algorithm is less than distributed algorithm but this comes at a cost of sustaining the fear of single point of failure in case of centralized algorithms. The intent is to reduce the memory requirement.

5. **Anchor placement**: The position where anchor is placed is also important. Some localization algorithm require anchor to be placed at corners of simulation area whereas some require anchor to be placed at Centre and start moving.

5.2 Fuzzy Logic

Fuzzy logic is a logical extension to multivalued logic permitting intermediate values to be defined between continuous evaluations such as yes or no, high or low, true or false etc.

A typical block diagram of fuzzy system is shown below in Figure 11:

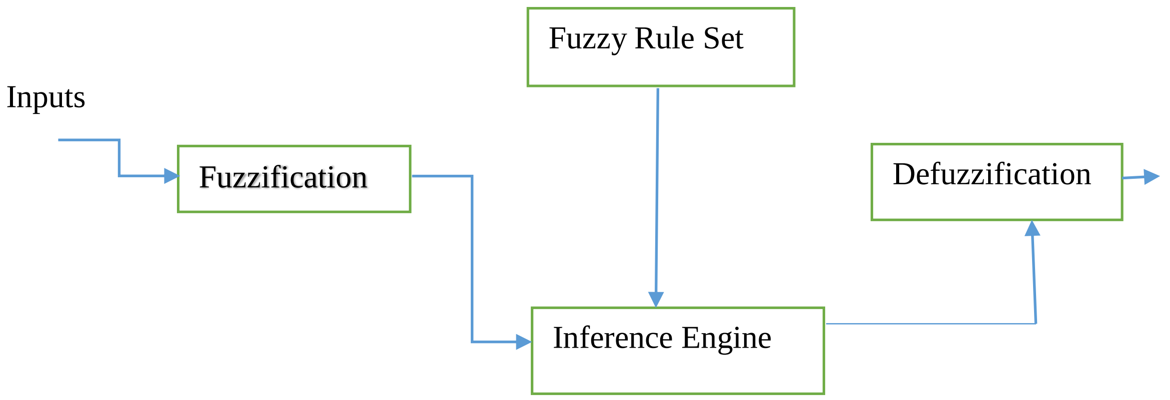

Figure 11: Fuzzy Inference System Block Diagram

There are numerous advantages of using Fuzzy logic: It is simpler to comprehend and less complex more intuitive; flexibility in terms of inputs and outputs, their range; number and types of membership functions; adjoined with traditional control paradigm.

Fuzzy logic offers an additional edge in solving the localization problem in wireless sensor networks because of following reasons:

1. Unlike probabilistic system, fuzzy system is not random. Rather it relies on complete understanding of the available dataset. Such situations come in handy to understand the behavior of sensor network.
2. Localization in wireless sensor networks is a nondeterministic problem. Thus modelling the network with certain fuzzification is simpler.
3. The nonlinear computations involved in calculating the accuracy or other factors involve some arbitrary computational inefficiency.

In this study, a rule set comprising of 5 rules have been incorporated into the Fuzzy Inference System (FIS). Empirical studies and experiments in some of the literatures suggested that accuracy of localization tends to improve with increase in number of membership functions and rule set. However there is no concrete evidence for this kind of uniform behavior. In other to minimize the memory requirements for additional rules, the number of rules should be kept minimum as possible. The rule set used for this study is as follows:

Rule 1: *IF RSSI is very low, THEN weight is very low*

Rule 2: *IF RSSI is low, THEN weight is low.*

Rule 3: *IF RSSI is medium, THEN weight is medium.*

Rule 4: *IF RSSI value is high, THEN weight is high.*

Rule 5: *IF RSSI value is very high, THEN weight is very high.*

Here, the Received Signal Strength Indicator (RSSI) has been calculated using equation:

$$RSSI\ [dBm] = RSSI_{src} - 10 * n * log_{10}(\frac{dist}{dist_{src}}) \tag{15}$$

$dist_{src}$ is taken to be 1m, $RSSI_{src}$ is RSSI value at a distance 1m and is taken to be -30dB. n is variable called path loss exponent and is taken to be 3.25.

The fuzzy inference system constructed is represented in block diagram shown in Figure 12:

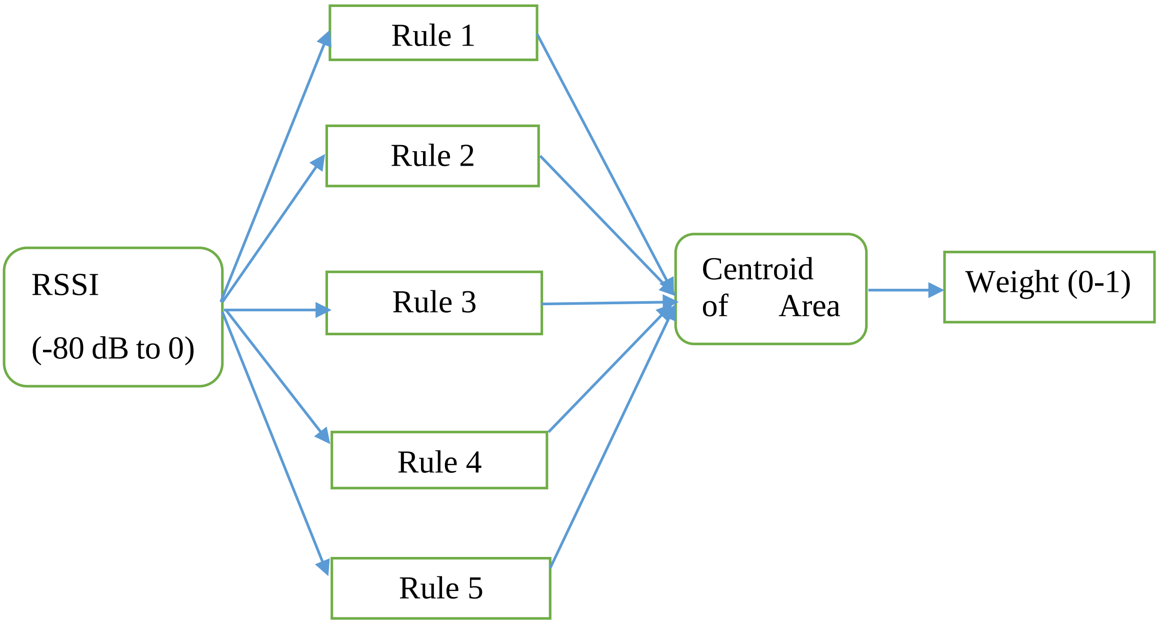

Figure 12: Inference Process Block Diagram

5.3 Weighted Centroid

Weighted centroid is an extension to the centroid localization technique presented in sec. 1.4.1. Weights denote the proximity or closeness of an unknown sensor node to a particular anchor. Greater the weight, more closely is the unknown sensor to that anchor. The accuracy of weighted centroid depends largely on the choice of weight. In the proposed scheme, the weights are output by the fuzzy system, thus relieving the network designer to manually assign weight to each anchor corresponding to its locations. Using weighted centroid, the position of an unknown node 'M' can be found as:

$$(\sum_{j=1}^{4} \frac{x_j w_j}{w_j}, \quad \frac{y_j w_j}{w_j})$$

With a tight upper bound on the approximation in Gauss Newton method and less number of anchors, the summated value of weights can be upper bound to be 1.

5.4 Gauss Newton Method

Gauss Newton optimization is used to solve nonlinear least square problems without having to compute the second differential. It requires the user to provide with the initial guess that is fed as an initialization vector to the optimization process.

Suppose we have 'M' functions f_a (a= 1,2,3,….., M) of N variables V (V_1,V_2,……). The Gauss Newton Optimization (GNO) can be used to minimal value of sum of squares.

$$S(V) = \sum_{a=1}^{M} f_a(V) \tag{16}$$

Initial guess: V [0]

$$V[k+1] = V[k] + \delta_k \tag{17}$$

where

$$\delta_k = -\left(J_f\right)^T * f \tag{18}$$

and $\mathbf{J_f}$ is the Jacobean matrix of 'f' with respect to the V[k].

In this study of the proposed scheme, the estimated position obtained from aggregated Sugeno-Mamdani FIS serves as the initial guess, say, $\boldsymbol{\psi_{di}}$.

$$\psi_i\,[k] = \psi_{di} \tag{19}$$

$$\psi_i\,[k+1] = \psi_i\,[k] + \delta_k \tag{20}$$

Here it must be noted that successive iteration involves computation of Jacobean, so the algorithm fails when singular matrix is obtained. Use of fuzzy logic estimated position as initial guess eliminates the odds of having to obtain a singular matrix.

5.5 Network Model

Wireless sensor network consists of a set of sensor nodes deployed randomly in large area to monitor the parameters of interest. These nodes are categorized as: anchor nodes and normal sensor nodes. Anchor nodes are special type of nodes embedded with GPS or other facility to obtain their position within the network. If feasible, these nodes can also be placed manually at known positions within the network. It is assumed that n numbers of anchor nodes are deployed in the sensing field. The position of anchor nodes is assumed as (X1, Y1), (X2, Y2),…., (Xn, Yn). Anchor nodes transmit periodic beacon signals containing information regarding their respective positions with overlapped region of coverage. Sensor nodes are deployed in the sensing field, with randomly distributed positions. These sensor nodes localize themselves with the help of beacon signals, transmitted by the anchor nodes. Each sensor node collects the received signal strength information (RSSI) of all connected adjacent anchor nodes through beacon signal and RSSI is used to obtain the edge weights of the anchor nodes for weighted centroid localization. Time division multiplexing (TDM) technique is used to avoid interference of beacons transmitted by neighboring anchor nodes. The radio transmission range of all nodes is assumed to be identical and perfectly spherical.

Figure 13 shows the flowchart of the steps involved in the proposed scheme. Here, it can be seen that the positions obtained from fuzzy logic weighted centroid is used as initial inputs for the Gauss Newton Method. Simulation results and their explanation has been mentioned in the subsequent chapter.

5.6 Flow Chart of the Proposed Scheme

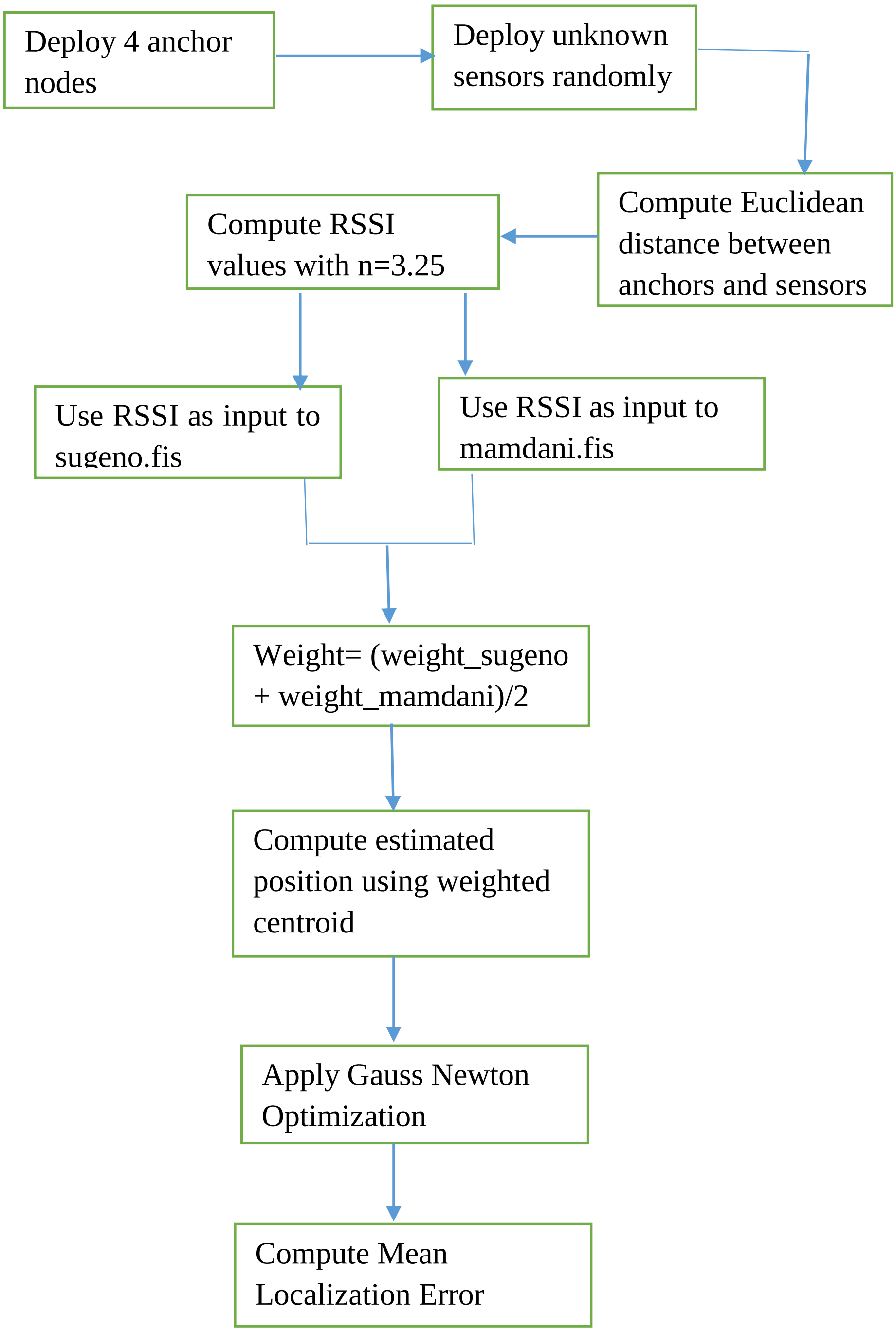

Figure 13: Flow Chart of Used Methodology

CHAPTER 6

RESULTS

The proposed approach was implemented in MATLAB 2012a using the fuzzy logic tool box. The various setup parameters were: the network area consisted of 10*10m, the number of unknown sensor nodes was ranging from 50 to 100 and the number of locator nodes or anchors were only 4. Each of the 4 anchor was placed at 4 corners of the network area i.e. the anchors were at (0, 0), (0, 10), (10, 0), (10, 10). The unknown nodes were randomly deployed. Various assumptions and parameters of consideration have already been discussed in chapter 5.

In the fuzzy logic toolbox, we modeled the Sugeno type and the Mamdani type separately and then computed the average of the output weight as depicted in flowchart of research methodology.

Figure 14 and Figure 15 show the fuzzy system created using Mamdani type logic. The input membership functions are triangular (*trimf*) and so is the output membership function. 5 rules were created based on the 5 membership functions, as discussed in section 5.2. The input variable i.e RSSI ranged from -80 to 0, where -80 is the minimum RSSI value and 0 is the maximum. The output i.e. weight value was between [0, 1].

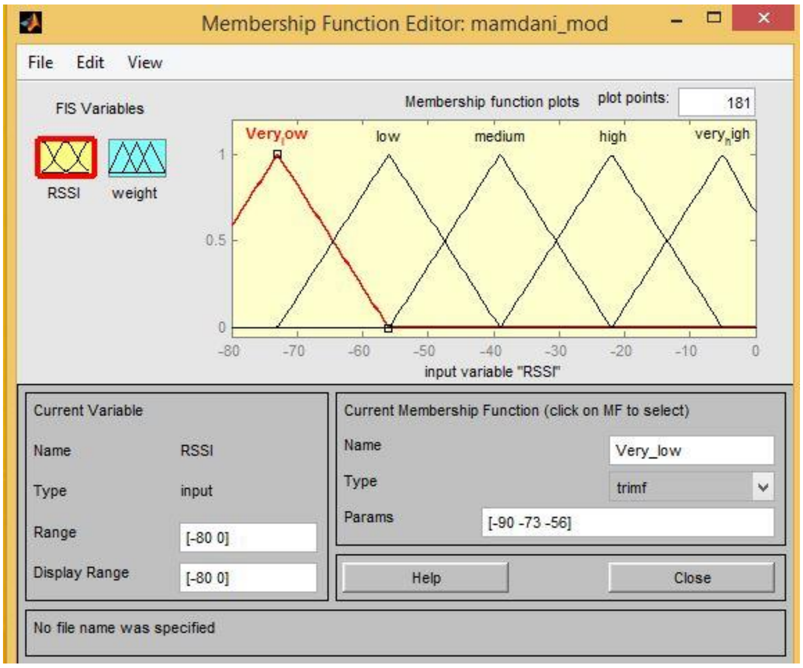

Figure 14: Mamdani Input Specification

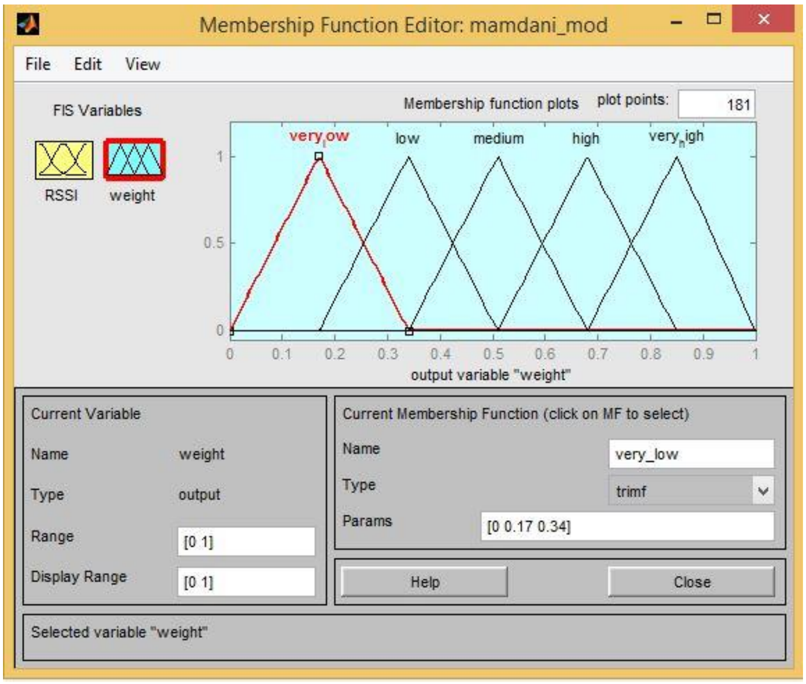

Figure 15: Mamdani Ouput Representation

Figure 14 and Figure 16 show the fuzzy system created using Sugeno type logic. The input membership functions were triangular (*trimf*) and the output membership functions are linear. The range of value was as follows: very low: [0,0.2], low: [0,0.4], medium: [0,0.6], high: [0,0.8], very high: [0,1] .

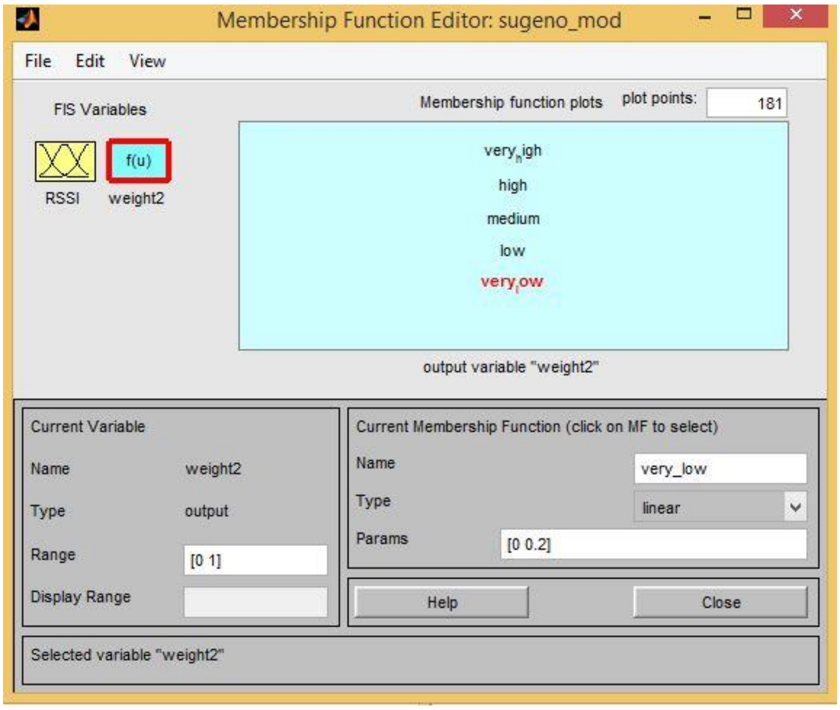

Figure 16: Sugeno Output Representation

Figure 17 and Figure 18 depicts rule viewer for Sugeno and Mamdani type respectively.

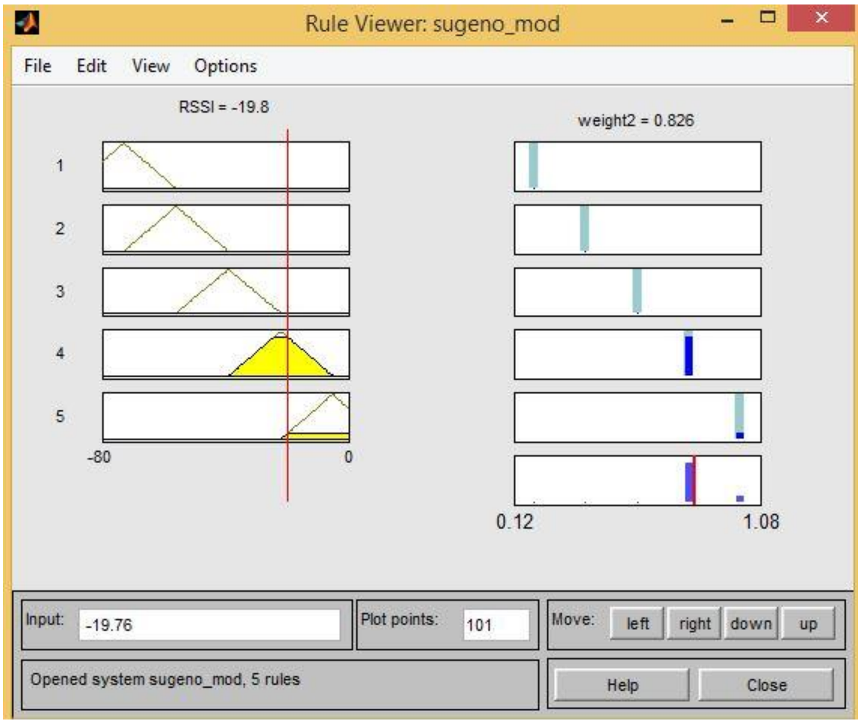

Figure 17: Rule Viewer: Sugeno Type

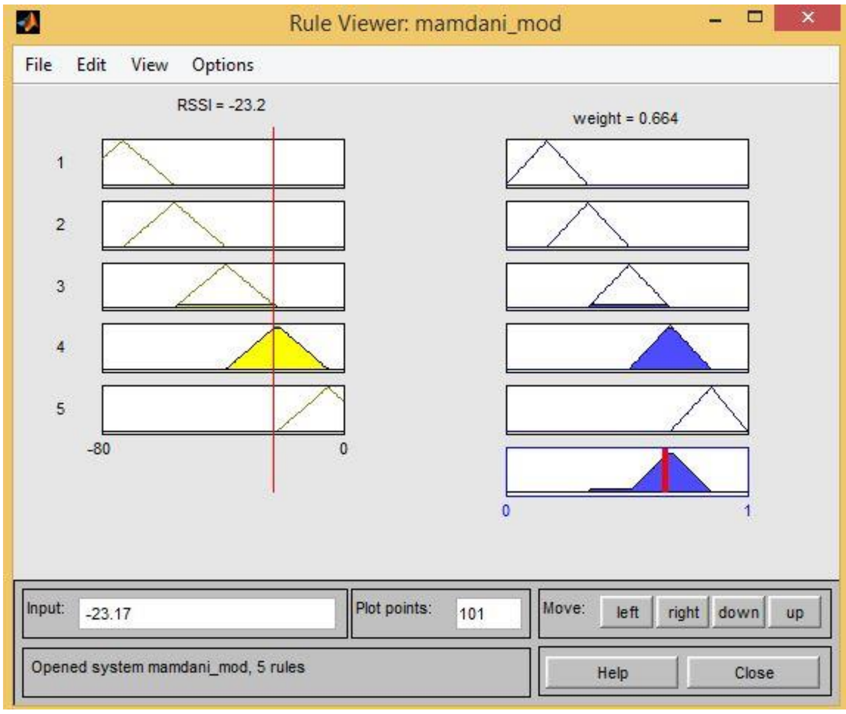

Figure 18: Rule Viewer: Mamdani Type

As it can be seen in Sugeno type when RSSI value is -19.8dBm, the weight is 0.826; and in the Mamdani type when weight is somewhere near to 0.7. Thus both types of Fuzzy Logic behave differently and the output depends on which FL type we are using.

Figure 19 shows the localization before employing the Gauss Newton optimization. This is node localization purely based on the average weight obtained from the Sugeno and Mamdani FL and fed into weighted centroid algorithm as discussed in section 5.3. The mean estimation localization error ranged from 3 to 4m, as different times simulations were run.

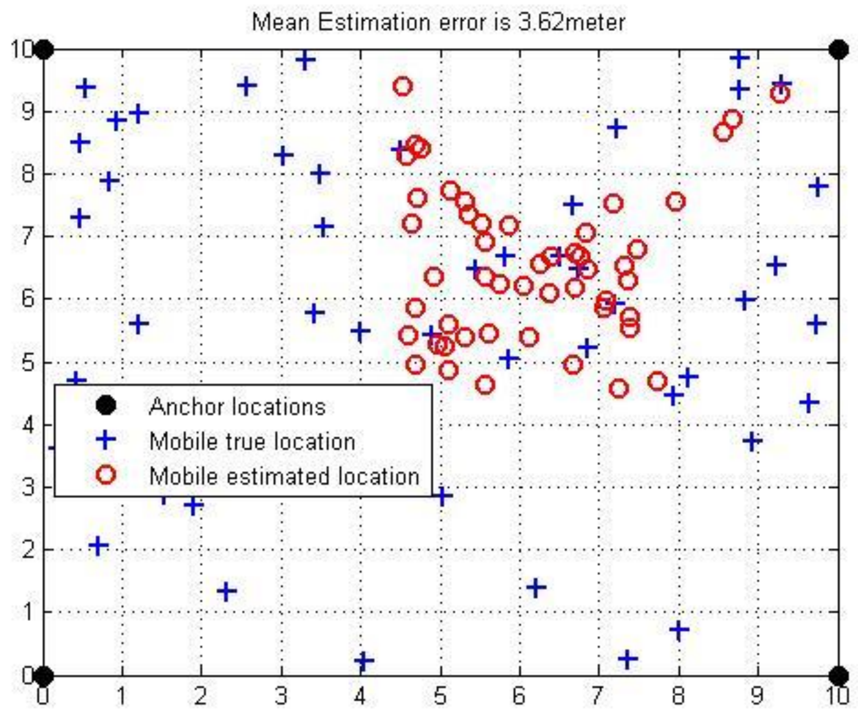

Figure 19: Localization before Gauss Newton Optimization

Figure 20 depicts the node localization after employing the Gauss Newton optimization. The procedure for the same and mathematical equations have been discussed in section 5.4. GN optimization improved the localization accuracy significantly by reducing the mean estimation error from ~3.5m to range of ~0.4m to 0.49m. Furthermore, since the least square problem formed contained only two variables, the running time complexity was also low. GN method optimizes a least square problem without having the user to compute the second order derivatives. So the overhead involved is also low.

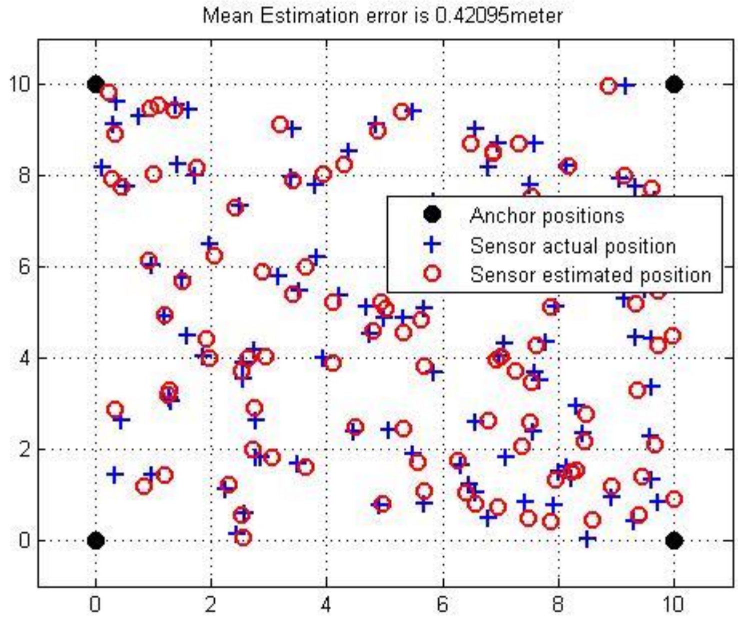

Figure 20: Localization after Gauss Newton Optimization

Figure 21 shows the plot of variation in Mean Estimation error vis-à-vis number of sensor nodes deployed. As it can be seen clearly, the men estimation error increased somewhat linearly from 0.12 to 0.32 as number of nodes increased from 10 to 60. Then there was a sharp increase in error as number of node increase to 60 to 70 and after that it became almost constant. Here it must be noted that this plot was drawn upon the results obtained empirically.

Figure 22 shows a bar chart of average localization error comparison of the proposed scheme with the existing works in soft computing based localization. As it can be inferred from the diagram that the mean localization error of simple centroid scheme was 1.61m and that of individual Mamdani FIS and Sugeno FIS was 0.90m and 0.95m respectively. A combined Mamdani and Sugeno approach yielded a localization error of nearly 0.77m. The mean localization error of proposed scheme is 0.43m. Also, here is worth mentioning that the studied existing works used an anchor ratio of at least 66.8% and up to a total of 121 anchors to localize 80 nodes. The proposed scheme used only a total of 4 anchors to achieve the localization of 100 randomly deployed node in an average time duration of within 3-4s in MATLAB. A tabular representation of comparison of existing schemes with proposed one has been depicted in Table 3.

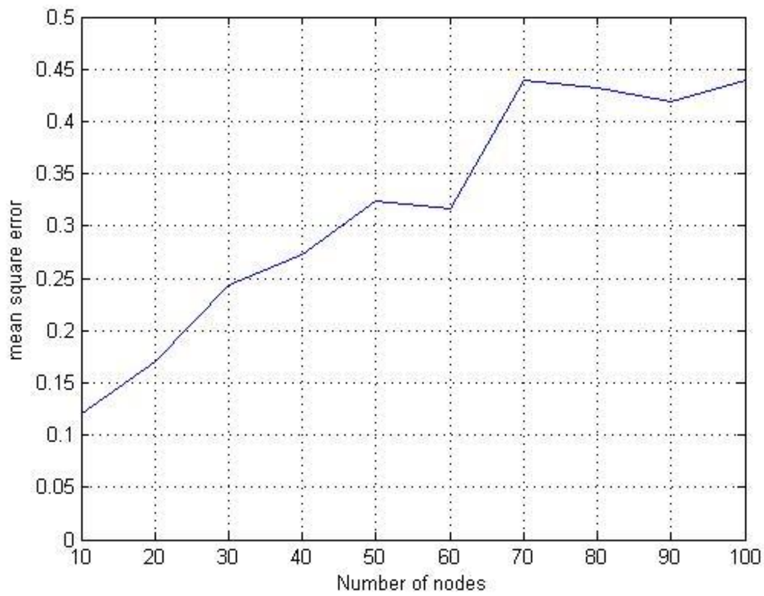

Figure 21: Mean error vs Number of nodes

6.1 Comparison with other Works:

Table 3: Comparison of other techniques with proposed one

Technique	Mean Estimation Error (in meters)	Number/Ratio of anchors
Simple Centroid [5]	1.6080	66.8%
Mamdani Fuzzy Logic [23]	0.8956	66.8%
Sugeno Type FL [25]	0.9462	66.8%
Sugeno-mamdami ANFIS [23]	0.7664	66.8%
Probabilistic Fuzzy [22]	1.9928	121
3 *trimf* ANFIS [27]	3.581	---
Proposed Scheme	0.45	4

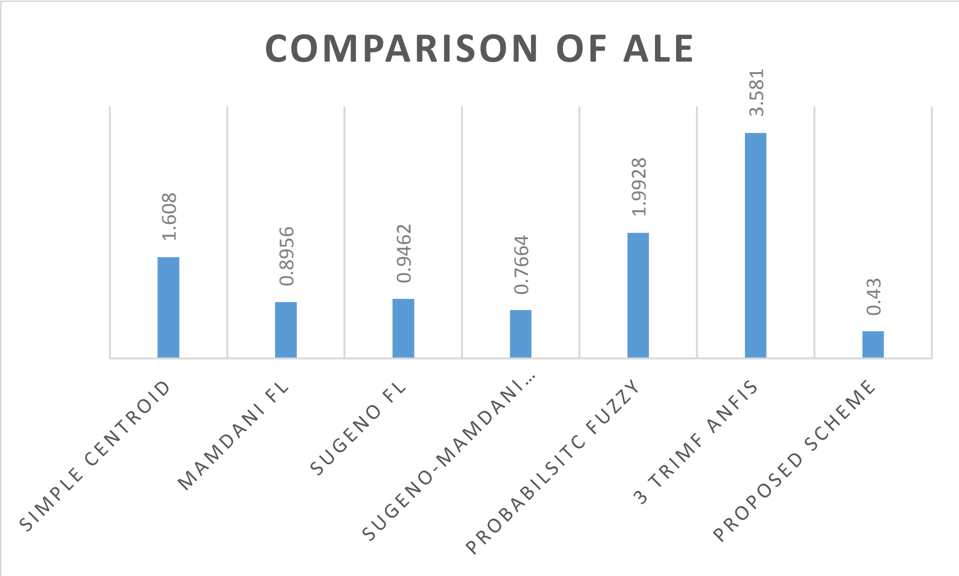

Figure 22: Comparison of ALE of various schemes

6.2 Discussion of Other Parameters

Apart from average localization error, the effectiveness of proposed scheme can also be assessed in terms of other parameters such as cost, running time complexity, localization coverage, scalability. Cost in context of localization majorly stems from the number of anchors deployed. The proposed scheme is intrinsically cost effective as it used only 4 anchors to localize 100 nodes. Running time of the proposed scheme is also promising, although the results may vary for different processing capabilities and hardware platforms. The proposed scheme localized on average at least 97 nodes out of 100 deployed to achieve a coverage of 97%. One major issue with the proposed scheme is scalability. The scheme does not scale well with large scale sensor node deployment in its present form. The solution to scalability bottleneck can be to implement this scheme by partitioning the large scale network into a number of clusters of 100 nodes each and implement this scheme for each cluster.

CHAPTER 7

CONCLUSION AND FUTURE WORK

With more than ever research being going on in the field of WSN and its application scenarios in Internet of Things (IoT) and robotics, localization problem poses challenge to all these applications. The problem of fading, attenuation, incorrect computations prompted the researchers to move from range based techniques to range free techniques. Soft computing techniques such as fuzzy inference systems, genetic algorithms, particle swarm optimization etc. effectively take into account the uncertainty and randomness in real world problems and handle them accordingly. Wireless sensor networks being non deterministic in nature, can conveniently be modeled using soft computing techniques. This study proposed a new fuzzy system based soft computing approach to solve the issue of node localization in wireless sensor networks. The position error was then optimized using Gauss Newton method to improve the mean localization error from nearly 3.5m to 0.45m. The proposed work is also cost effective since it used only 4 anchors to localize successfully with a promising localization coverage.

Future work in this regard can be done to integrate the fuzzy logic approach towards localization with other optimization techniques such as ant colony optimization. The position information obtained from fuzzy logic can be used as initial input to ACO. Another open problem in this regard is that how can one modify the classification methodology of deep learning paradigms to use them in context of localization and other aspects of wireless sensor networks. Furthermore work can be done to achieve better localization results in presence of hurdles or in irregular deployment. The sole purpose is to achieve an accurate position of sensors with minimal cost (in terms of anchor), minimal power consumption, minimum space and time complexity.

CHAPTER 8

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APPENDIX A

GAUSS MARKOV MOBILITY

Mobility in ad hoc and sensor networks can be modeled using techniques such as Random Way Point (RWP) and Gauss Markov mobility model. Because of being light weight and better fit for nondeterministic networks, this study uses Gauss Markov Model. We assume that movement occurs at fixed time intervals say 'n'. So the velocity and orientation or direction of mobile node at n^{th} instant can be represented as:

$$S_n = \alpha * S_{n-1} + (1-\alpha)\bar{S} + \sqrt{(1-\alpha^2}\, S_{X_{n-1}} \tag{1}$$

$$d_n = \alpha * d_{n-1} + (1-\alpha)\bar{d} + \sqrt{(1-\alpha^2}\, d_{X_{n-1}} \tag{2}$$

Where α is the turning parameter with value range $0 \leq \alpha \leq 1$

If α=0, that means completely random movement.

And α=1 means linear movement.

$\bar{S}$ and $\bar{d}$ are the mean values of velocity and direction respectively.

Location of the node at any instance't' can be represented as:

$$X_t = X_{t-1} + S_{t-1}\ cos(d_{t-1}) \tag{3}$$

$$Y_t = Y_{t-1} + S_{t-1}\, sin(d_{t-1}) \tag{4}$$

Where $0 \leq d \leq 2\pi$

We begin the movement at center of the area. Movement time is 1000s. Time interval n is set to 1s. Assume α is 0.75. $S_{X_{n-1}}$ and $d_{X_{n-1}}$ will be computed from equation (8) which represents a Gaussian distribution with value of μ as 0 and standard deviation σ as 1. $\bar{S}$ is fixed to be 10 m/s and $\bar{d}$ is 90 degrees.

$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\mu}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{5}$$

χ is the random variable with normal distribution or Gaussian function of distribution, σ is the standard deviation of input data, σ^2 is variance and μ is the mean or median or mode as applied.

APPENDIX B

SIMULATION RESULT DATA

A sample data of weight value obtained from the joint Sugeno-Mamdami Fuzzy system using RSSI as input and triangular membership functions (*trimf*) in MATLAB^{TM} fuzzy toolbox for 100 deployed node is given below. **Note that the data is strictly empirical and different set of values will be obtained for different implementations**.

RSSI values are:

Columns 1 through 8

-63.5146	-57.9941	-64.7787	-43.6988	-54.9259	-55.3798	-60.5929	-62.0017
-61.0136	-59.6217	-62.4454	-58.3587	-64.4721	-54.0043	-63.8126	-39.6709
-57.2923	-55.2636	-57.3917	-62.1202	-50.1027	-60.8756	-46.7759	-65.5922
-48.2927	-57.5464	-45.9679	-65.0441	-63.5053	-60.2773	-58.2674	-59.5397

Columns 9 through 16

-62.6222	-54.2112	-59.8180	-61.8265	-60.4126	-62.8107	-35.2852	-59.4994
-51.3017	-57.9338	-65.9659	-58.4846	-43.6937	-46.3900	-61.8133	-60.4980
-63.3776	-57.9142	-37.9147	-58.3478	-64.5059	-64.9188	-60.5028	-54.2512
-54.4482	-60.3443	-62.3645	-51.5651	-59.5075	-57.1081	-65.9897	-56.2091

Columns 17 through 24

-59.6241	-57.6124	-58.1434	-59.4512	-64.6339	-56.7804	-54.8725	-33.4846
-57.6134	-47.9377	-46.2866	-55.0734	-61.7504	-59.9522	-50.2459	-60.7840
-57.9300	-63.5521	-64.0413	-59.9530	-58.1101	-54.8929	-64.2059	-61.8240
-55.2581	-60.8139	-60.9710	-55.9797	-44.9368	-58.8075	-63.2383	-66.1462

Columns 25 through 32

-59.4756	-63.5698	-52.0523	-62.3396	-62.9010	-54.4124	-58.1998	-61.5672
-65.5295	-51.2866	-59.5450	-60.8148	-48.3226	-62.1109	-63.5331	-63.7448
-40.0134	-64.1362	-57.0543	-56.0024	-64.5120	-52.8066	-47.5605	-48.2753
-61.9575	-54.0361	-61.6982	-51.4286	-56.1309	-61.6111	-60.3207	-56.8639

Columns 33 through 40

-62.3454	-58.5980	-62.6739	-37.4796	-57.6405	-54.2737	-47.0973	-52.9625
-47.0837	-60.8715	-65.2597	-60.2301	-60.0637	-58.4367	-61.3574	-55.8328
-64.4644	-53.3901	-44.2461	-61.5731	-54.6383	-57.3779	-57.5300	-60.2906
-56.9452	-57.5188	-58.0041	-65.6970	-58.0730	-60.3224	-63.9739	-61.4448

Columns 41 through 48

-58.7054	-64.7125	-38.8269	-62.0544	-59.5890	-62.7780	-61.3060	-57.6664
-64.8800	-63.4183	-62.5910	-60.8569	-44.8967	-65.6809	-62.1254	-55.3954
-43.3781	-55.6303	-59.5867	-55.6066	-64.1891	-42.0892	-52.4232	-59.5213
-61.6262	-49.0422	-65.9905	-52.1282	-59.8911	-58.7129	-54.9646	-57.8438

Columns 49 through 56

-58.0859	-57.5325	-62.9579	-50.2419	-60.0434	-64.3094	-65.5691	-53.8506
-64.9359	-57.6376	-60.7683	-60.3130	-38.1900	-55.0933	-61.3700	-53.5561
-44.4315	-57.5793	-56.8498	-57.0663	-65.6362	-63.2382	-60.2248	-61.8037
-62.1712	-57.6837	-49.7594	-62.6433	-61.6412	-49.9165	-38.1350	-61.7096

Columns 57 through 64

-53.1201	-63.2915	-42.3656	-66.6952	-62.2699	-59.7010	-43.0551	-52.8871
-60.0527	-59.1881	-58.7019	-61.7356	-60.2538	-57.2026	-60.1658	-63.0132
-56.0331	-59.1304	-62.3524	-61.9069	-56.7153	-58.3442	-59.9414	-52.9992
-61.2882	-47.9437	-65.3870	-24.6722	-51.1436	-55.1799	-64.6216	-63.0400

Columns 65 through 72

-54.7466	-66.3505	-65.6420	-64.9533	-62.4066	-51.6738	-63.8220	-61.6539
-61.1235	-62.5599	-60.3624	-62.6151	-58.1053	-60.5249	-62.8706	-53.1481
-53.9473	-60.3480	-61.3623	-57.4786	-59.2277	-56.1846	-54.8044	-61.9731
-60.8106	-34.9042	-37.5084	-45.6334	-50.3432	-62.1297	-50.5517	-54.1614

Columns 73 through 80

-51.7115	-63.3878	-57.6818	-56.2931	-61.2192	-62.4622	-65.1363	-58.8484
-56.1927	-49.4414	-64.4873	-60.6839	-61.0234	-66.9304	-62.5107	-57.3633
-60.5001	-64.5732	-45.8939	-53.9530	-54.4756	-22.9710	-57.9933	-57.9649
-62.1048	-55.3795	-61.8737	-59.5246	-53.9548	-61.6177	-44.3741	-56.2559

Columns 81 through 88

-63.8410	-60.0054	-60.3761	-60.1344	-56.6682	-57.4139	-64.7629	-54.1028
-63.4897	-40.1739	-35.7530	-48.4788	-60.9426	-58.6800	-61.5461	-63.0727
-53.5547	-65.2237	-65.9792	-63.2142	-53.4468	-56.4528	-58.6020	-51.9151

-51.9039	-61.0218	-61.9092	-57.9987	-59.3679	-57.8860	-43.8479	-62.5242

Columns 89 through 96

-51.0940	-55.4321	-60.7716	-62.1107	63.4627	-47.3921	-54.3225	-60.8281
-62.3514	-61.1642	-60.3128	-13.9312	-60.2338	-57.5209	-60.2884	-45.3764
-54.7754	-53.5663	-55.2496	-67.0778	-58.2075	-61.2066	-55.2296	-64.2168
-63.2695	-60.3962	-54.2044	-62.2681	-47.7393	-63.8384	-60.6922	-58.5908

Columns 97 through 100

-62.2656	-61.3248	-45.8119	-45.1512
-48.8251	-58.5088	-58.6950	-61.8208
-63.9561	-57.9267	-60.5144	-57.9930
-56.1360	-52.5602	-64.0410	-64.6215

Weights are:

Columns 1 through 7

0.2873	0.3452	0.2747	0.5007	0.3838	0.3781	0.3168
0.3124	0.3271	0.2979	0.3411	0.2778	0.3948	0.2843
0.3536	0.3795	0.3524	0.3012	0.4366	0.3139	0.4697
0.4547	0.3505	0.4777	0.2721	0.2873	0.3201	0.3421

Columns 8 through 14

0.3024	0.2961	0.3923	0.3250	0.3041	0.3187	0.2943
0.5463	0.4243	0.3460	0.2630	0.3396	0.5008	0.4735
0.2667	0.2886	0.3462	0.5689	0.3412	0.2774	0.2734
0.3280	0.3895	0.3194	0.2987	0.4215	0.3283	0.3558

Columns 15 through 21

0.5989	0.3284	0.3271	0.3498	0.3435	0.3289	0.2762
0.3043	0.3178	0.3497	0.4582	0.4745	0.3819	0.3049
0.3178	0.3919	0.3460	0.2869	0.2820	0.3235	0.3439
0.2627	0.3672	0.3796	0.3145	0.3129	0.3703	0.4880

Columns 22 through 28

0.3599	0.3844	0.6177	0.3287	0.2867	0.4164	0.2990
0.3236	0.4351	0.3148	0.2673	0.4244	0.3279	0.3145
0.3842	0.2804	0.3042	0.5420	0.2811	0.3565	0.3700
0.3360	0.2900	0.2612	0.3028	0.3944	0.3054	0.4230

Columns 29 through 35

0.2933	0.3899	0.3429	0.3068	0.2989	0.3384	0.2956

0.4544	0.3013	0.2871	0.2850	0.4666	0.3139	0.2700
0.2774	0.4083	0.4619	0.4548	0.2779	0.4018	0.4951
0.3683	0.3063	0.3197	0.3589	0.3578	0.3509	0.3451

Columns 36 through 42

0.5741	0.3494	0.3916	0.4665	0.4065	0.3372	0.2754
0.3206	0.3224	0.3402	0.3089	0.3722	0.2737	0.2882
0.3067	0.3872	0.3526	0.3507	0.3200	0.5041	0.3748
0.2656	0.3443	0.3196	0.2827	0.3080	0.3062	0.4472

Columns 43 through 49

0.5573	0.3018	0.3275	0.2946	0.3094	0.3491	0.3442
0.2964	0.3141	0.4884	0.2658	0.3011	0.3779	0.2732
0.3275	0.3751	0.2806	0.5179	0.4124	0.3282	0.4932
0.2627	0.4156	0.3242	0.3371	0.3833	0.3470	0.3007

Columns 50 through 56

0.3507	0.2928	0.4352	0.3226	0.2794	0.2669	0.3965
0.3495	0.3150	0.3197	0.5655	0.3817	0.3088	0.3999
0.3501	0.3590	0.3563	0.2663	0.2900	0.3207	0.3044

0.3489	0.4400	0.2959	0.3060	0.4385	0.5662	0.3053

Columns 57 through 63

0.4048	0.2895	0.5149	0.2557	0.2997	0.3262	0.5075
0.3225	0.3318	0.3372	0.3051	0.3204	0.3547	0.3213
0.3696	0.3324	0.2988	0.3033	0.3607	0.3412	0.3237
0.3096	0.4581	0.2687	0.7075	0.4259	0.3806	0.2763

Columns 64 through 70

0.4074	0.3859	0.2591	0.2662	0.2730	0.2983	0.4204
0.2922	0.3113	0.2968	0.3192	0.2962	0.3440	0.3175
0.4061	0.3954	0.3194	0.3089	0.3514	0.3314	0.3676
0.2920	0.3145	0.6030	0.5738	0.4810	0.4341	0.3011

Columns 71 through 77

0.2842	0.3059	0.4200	0.2885	0.3489	0.3662	0.3103
0.2937	0.4045	0.3675	0.4432	0.2776	0.3159	0.3123
0.3852	0.3027	0.3178	0.2768	0.4784	0.3954	0.3892
0.4320	0.3929	0.3013	0.3781	0.3037	0.3281	0.3953

Columns 78 through 84

0.2977	0.2712	0.3356	0.2840	0.3230	0.3191	0.3216
0.2533	0.2973	0.3527	0.2875	0.5400	0.5938	0.4528
0.7275	0.3453	0.3456	0.3999	0.2703	0.2628	0.2902
0.3063	0.4937	0.3666	0.4180	0.3124	0.3033	0.3452

Columns 85 through 91

0.3613	0.3521	0.2749	0.3936	0.4264	0.3774	0.3149
0.3132	0.3374	0.3070	0.2916	0.2988	0.3109	0.3197
0.4011	0.3641	0.3383	0.4179	0.3856	0.3998	0.3797
0.3298	0.3465	0.4992	0.2971	0.2897	0.3189	0.3924

Columns 92 through 98

0.3013	0.2878	0.4636	0.3910	0.3144	0.2997	0.3093
0.8244	0.3206	0.3508	0.3200	0.4836	0.4494	0.3394
0.2518	0.3428	0.3105	0.3800	0.2803	0.2829	0.3460
0.2997	0.4601	0.2840	0.3158	0.3384	0.3682	0.4109

Columns 99 through 100

0.4792	0.4859
0.3373	0.3042
0.3176	0.3453
0.2820	0.2763

APPENDIX C

PUBLICATIONS

- Abhishek Kumar, Deepak Prashar, " A novel approach for node localization in wireless sensor networks", Proceedings of International Conference on Intelligent Communication, Control and Devices,2017, *Advances in Intelligent System and Computing*, Springer ***{Scopus, DBLP}***
- Abhishek Kumar, Deepak Prashar, "A Sugeno- Mamdani Fuzzy System Based Soft Computing Approach towards Sensor Node Localization with Optimization", *Journal Of Networks and Computer Applications*, Elsevier B.V (**Communicated**)
- Abhishek Kumar, Deepak Prashar, "Localization Techniques in Wireless Sensor Networks: A Review*", International Journal of Advanced Research in Computer and Communications Engineering*, Volume 5 Issue 8, 2016