International Journal of
Intelligent Systems and Applications in Engineering

ISSN:2147-6799 www.ijisae.org Original Research Paper

RSSI and Flower Pollination Algorithm Based Location Estimation for Wireless Sensor Networks

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Accepted 3rd September 2016

Abstract: Wireless Sensor Networks (WSN's) have been finding to itself new applications continuously. Many of these applications need location information of nodes. The localization of nodes can be made by range based or range free localization methods conventionally. Angle-of-Arrival (AoA), Time-Difference-of-Arrival (TDoA), Received Signal Strength Indicator (RSSI), Time-of-Arrival (ToA) are well known range based methods. Therefore AoA, ToA and TDoA have some hardware and software difficulties for nodes which have limited processing and power sources. However RSSI based localization doesn't cost high processing resources or complex hardware modifications. Most of the WSN nodes already have RSSI measurement capability. However RSSI measurements is vulnerable to noise and environmental effects. Therefore error of RSSI based localization can be over to an acceptable level.

Centroid, APIT, DV-Hop and Amorphous are some of the range free localization methods. Range free methods can only give location information approximately but they don't need any extra hardware or high processing capability.

In this study WSN nodes are assumed randomly or regularly distributed on a certain area. Some of the nodes are beacon nodes. The beacon nodes are assumed as having higher power resources and GPS receivers. The locations of nodes are assumed as fixed. The beacon nodes send their location information sequentially. Localization of nodes are made through RSSI and location information of beacon nodes. The mean of RSSI is calculated to reduce effect of noise on it. A rough location estimation made by weighted centroid. A probabilistic based location estimation and flower pollination algorithm (FPA) are used separately to make final decision about the location. Rough estimates are used to limit search area of flower pollination algorithm in order to reduce convergence time.

Keywords: *RSSI, FPA, WSN, optimization, probabilistic.*

1. Introduction

Recently, WSN has become popular study in communication. The apps like health, business, military and habitat are the factors which made WSN has been so popular [1]. Nodes which are the elements of the WSN have advantages as operating with low-power, having small physical structure, low-cost and communication capability with adjacent nodes in limited range [2]. These are the other reasons why the WSN is so popular.

One of the main objective about WSN is acquiring location information of the sensor nodes. The localization simply means determining physical coordinates of the nodes which are unknown. Location information of the sensor nodes carry vital weight for many WSN apps. For instance; monitoring and surveillance of volcano activities, tsunami risk in oceans, melting regime of the poles, wild animals under risk of extinction, mobility of civilian and military vehicles and agricultural fields require that.

In WSN's, there are two typical node types. Anchor node (also is called Beacon) is one of them. Anchor node knows location information of itself and can send data to the adjacent nodes. Other one is called non-anchor node which estimates physical coordinates of itself by various methods through location information of the anchor nodes that are in coverage area of it.

In literature, various localization methods have been classified conventionally into two categories named as range-based and range-free methods. Range-based methods require additional hardware. Naturally, additional hardware makes it costly.

Angle-of-Arrival (AoA), Time-Difference-of-Arrival (TDoA), Received Signal Strength Indicator (RSSI), Time-of-Arrival (ToA) are well known range based methods. AoA needs angle of received signal, time based methods; ToA needs exact synchronization between nodes, TDoA needs multiple receivers and synchronization between these receivers [3]. Therefore AoA, ToA and TDoA have some hardware and software difficulties for nodes which have limited processing and power sources.

Range-free methods generally use hop-counting and local techniques [4]. As a feature Range-free methods don't require additional hardware but location estimations are rougher than range-based methods. Centroid, APIT, DV-Hop and Amorphous are some of the range-free localization methods [5]-[6]-[7].

If RSSI based localization is taken into account, it is seen that it doesn't require high processing resources or complex hardware modifications. Even it can be considered the least complex among the range-based methods. Most of the WSN nodes already have RSSI measurement capability. But on the other hand RSSI measurements are under effects of noise and environment. Therefore error of RSSI based localization should be over to an acceptable level. For the RSSI based localization, noise and environmental effects are considerable problems. To reduce these effects, there are many methods have been proposed in literature. Some studies are based on reducing of distance error by estimating of path loss parameters dynamically [8]-[9]. In another study, error is reduced by making a mapping database between

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Note: This paper has been presented at the 3rd International Conference on Advanced Technology & Sciences (ICAT'16) held in Konya (Turkey), September 01-03, 2016.

RSSI and distance information [10]. On the other hand, particle filter usage may has been another solution for RSSI error. For instance, in reference [11] a new particle filter with a hardware-free initialization phase is presented. In other particle filter approach, multiple antenna arrays and particle filter are used together for reducing of RSSI error [12].

In this study, locations of nodes are assumed as fixed. Namely, environment is assumed as static. Therefore, path loss attenuation is also assumed a fixed value. In simulation scenario, the beacon nodes send their location information sequentially. Location estimations of the nodes are made through RSSI and location information of beacon nodes. The mean of RSSI measurements are calculated to reduce effect of noise on it. A rough location estimation made by weighted centroid. In the next phase, a probabilistic based location estimation and flower pollination algorithm (FPA) are used separately to make final decision about the location. Rough estimates are used to limit search area of flower pollination algorithm in order to reduce convergence time.

2. Received Signal Strength

RSSI method is based on location estimations of the non-anchor nodes by using signal strength of the anchor nodes where are in coverage area of the non-anchor nodes. Received Signal Strength (RSS) can be formulated simply shown as in (1).

$$RSS(dB) = P_{TX}(dB) - P_{LOSS}(dB) \tag{1}$$

Where, $RSS(dB)$ is received signal strength acquired at non-anchor node, $P_{TX}(dB)$ is transmitter power of the anchor node, $P_{LOSS}(dB)$ is path loss in the channel. Well-known models for path loss are Free Space, Log-normal and Hata [13]. Generally, environment where is WSN modules installed shows distortion effects like diffraction, multipath, obstacles etc. The most convenient path loss model for these kind of environments is Log-normal distance model [14]. In this model, path loss can be calculated through the equation shown as in (2).

$$P_{LOSS}(d) = \overline{P_{LOSS}}(d_0) + 10\delta\log(\frac{d}{d_0}) + X_0 \tag{2}$$

Where, $P_{LOSS}(d)$ is path loss value in dB that occurred at distance d, X_0 is Gaussian noise with zero mean and standard deviation can vary between 4~10. δ is path loss attenuation factor which can vary between 2~5. $P_{LOSS}(d_0)$ is path loss value in dB that occurs at 1m distance. $P_{LOSS}(d_0)$ is given 40.3dB in CC2538 catalogue [15]. Therefore we accepted $P_{LOSS}(d_0)$ =40.3dB.

In simulations, a fixed path loss attenuation factor (*δ)* is used because of anchor and non-anchor nodes are assumed to be fixed locations. In this conditions, path loss is under effect of Gaussian noise as seen in equation (2).

2.1. The Improvement of RSS Quality

First phase of proposed system is about improvement of RSS quality. Absolute uncalibrated RSSI/CCA accuracy is ±4dB in CC2538 catalogue [15]. This accuracy means ±8m location error at 25m distance under certain conditions. For some apps that accuracy is acceptable but not always. To reduce noise and improve the accuracy, anchor nodes should send signal sequences to its non-anchor nodes. Each non-anchor node gets RSS sequences from the anchor nodes that are at coverage area of it. Due to nodes are static, distances don't vary. In that case, mean of each RSS sequence is an improved RSS information because of Gaussian noise reduced. This is expressed mathematically in equation (3).

$$RSS_{IMP} = \frac{\sum_{i=1}^{k} RSS_i}{k} \tag{3}$$

Where, RSS_{IMP} is improved RSS value that is acquired from anchor node, k is the number of sequence, RSS_i is the ith RSS value that is acquired from anchor node. Improved RSS information is important for the distance information. For the next phase of the proposed system, distance can be calculated shown as in equation (4).

$$d_i = 10^{\frac{(P_{TX} - RSS_{IMPi} - \overline{P_{LOSS}}(d_0))}{10\delta}} \tag{4}$$

Where, d_i is ith improved distance information of the anchor node which is in coverage area of the adjacent non anchor node.

Improved distance information is one of the important parameter for the applied pre-localization. In this study, we preferred weighted centroid algorithm (because of its simplicity).

3. Weighted Centroid

Weighted centroid is a RSS based localization algorithm [16]. Weights specify level of proximity of the anchor nodes according to the non-anchor node. Weights can be calculated shown as (5).

$$w_i = \frac{\sum_{i=1}^{N} d_i}{N.d_i} \tag{5}$$

Where, w_i is the weight of ith anchor node and N is the anchor node number in the coverage area. After calculation of the weights, rough coordinates can be calculated shown as in equation (6).

$$x_r = \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i}, \quad y_r = \frac{\sum_{i=1}^{N} w_i . y_i}{\sum_{i=1}^{N} w_i} \tag{6}$$

Where, x_i is abscissa of the ith anchor node, y_i is ordinate of the ith anchor node, x_r is abscissa of the estimated rough coordinates and y_r is ordinate of the estimated rough coordinates. Even if, the coordinates that are estimated through weighted centroid might be sufficient for many WSN apps, sometimes it might not be sufficient. Hence at the last step, probabilistic and FPA methods are used for the improvement.

4. Probabilistic Approach

In this approach non-anchor nodes estimate their own location through probability density function (pdf). We can express the probability of non-anchor node location in limited area at two dimensional space as in (7).

$$P_R(x_n, y_n) = \int_{y_n-\Delta y}^{y_n+\Delta y} \int_{x_n-\Delta x}^{x_n+\Delta x} f_{X,Y}(x,y)\,dx\,dy \tag{7}$$

Where, $P_R(x_n, y_n)$ is the probability of the non-anchor node, x can change between x_{min} and x_{max} and y can change between y_{min} and y_{max} which are bounding coordinates. Δx and Δy are arbitrary small values [17].

The first phase of this approach is calibration phase. RSS measurements are collected at different distances between anchor and non-anchor node. The mean value of RSS measurements $\mu_{RSS}(d)$ and standard deviation $\sigma_{RSS}(d)$ can be calculated from measurements, where d defines distance. In reference [17] it is mentioned that in theory and experiments σ_{RSS} doesn't vary significantly with the distance. If X_0 is 0, RSS probability of any distance d' is equal to 1.

$$p \to P_R\left\{ d' = 10^{\frac{(P_{TX} - RSS - \overline{P_{LOSS}}(d_0))}{10\delta}} \right\} = 1 \quad (8)$$

Practically, channel is under effect of shadowing. Thereby, distribution of distance for a fixed RSS value is log-normal. Consequently in calibration phase, log-normal mappings of the RSS measurements are acquired [17].

Second phase of the probabilistic approach is localization with positive constraints. In this phase, each non-anchor node estimates its pdf position through the log-normal mappings of the RSS measurements.

At first, each non-anchor sets initial estimation for entire network area. Then, anchor nodes send information which includes their own position information and updated pdf estimations of both their own and non-anchors to the adjacent nodes. Non-anchor receives the information and executes the following algorithm;

- RSS measurement is done from received packets,
- RSS is mapped to the one dimensional pdf acquired from the first phase, and a pdf constraint is generated which is function of the 2D coordinate.
- Old pdf is intersected with generated constraint and update is done.
- At last, non-anchor node sends updated pdf estimation to all its adjacent nodes.

Consequently, final estimations for the non-anchor node coordinates are made according to the maximum probability evaluation.

5. Flower Pollination Algorithm(FPA)

Pollination process in the nature consists of two different forms called biotic and abiotic forms. Biotic pollination is carried out by pollinator creatures as bird, bat and bee. 90% of all pollination events take place in biotic form. And remaining 10% happens in abiotic form that is occurred by wind or water diffusion. It does not include any pollinators. Pollinators travel to long distances to reach plants that they wish. They maximize the pollination probability of the same-species via flying over other species. Pollination process happens in two main types as self-pollination and cross-pollination. Self and cross-pollination are shown in (Figure.1).

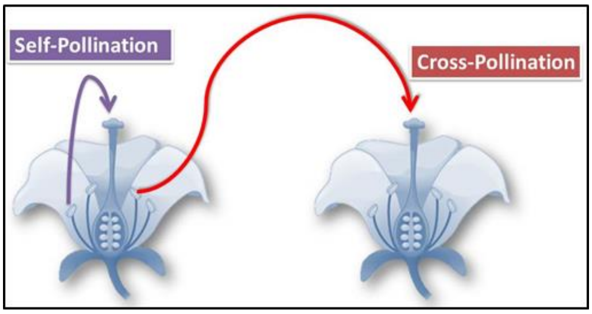

Figure 1. Pollination Types

Cross-pollination is defined as pollination that occurs among different plants in the same species. Thus, pollinators are very effective for the cross-pollination. On the other hand, if the pollination occurs in the same plant, this is defined as self-pollination. While self-pollination might occur in different flowers of the same plant, it might also occur in same flower of the same plant [18].

Pollinators like bird, bat and bee show Lévy Fligt behaviour and flying steps show Lévy distribution [19]. Pseudo algorithm of the FPA can be expressed as below

Rule (1): Biotic-cross-pollination is accepted as global pollination process. Pollinators who carry pollens show Lévy Flight behaviour.

Rule (2): Abiotic-self-pollination is accepted as local pollination process.

Rule (3): Flower pollination constancy is proportional with the probability of breeding between two similar species.

Rule (4): Global and local pollination probability is controlled by a switching probability which is defined as p ∈ [0, 1]. The effects like physical proximity, wind and local pollination are considerable part of the global pollination. As a result, they are also considerable for the switching probability. In other words, these effects can be changed by controlling switching probability.

In global pollination phase, the most convenient pollination can be achieved by pollinators who can travel to long distances. While the most convenient pollination parameter is g_b, flower pollination constancy can be expressed mathematically as in (9).

$$\phi_i^{t+1} = \phi_i^t + L\left(\phi_i^t - g_b\right) \quad (9)$$

Where, ϕ_j^t is the ith solution vector in tth iteration, g_b is the best solution in tth iteration and L is the step size which is characterized by Lévy Flight [18-19].

Flower constancy for local pollination can be expressed mathematically as in (10).

$$\phi_i^{t+1} = \phi_i^t + \in\left(\phi_j^t - \phi_k^t\right) \quad (10)$$

Where ϕ_j^t and ϕ_k^t defines pollens where they come from different flowers of the same plant species. If ϕ_j^t and ϕ_k^t come from the same species or selected from the same population, it shows random walk characteristics with uniform distrubition as defined ϵ [0, 1] [18]. Consequently, flow chart of FPA can be drawn as shown in (Figure.2).

In this study unlike the conventional FPA algorithm, rough solutions and improved data are integrated to the algorithm. Objective function of this optimization phase is expressed in equation (11).

$$J(x,y) = \sum_{i=1}^{k} \frac{\left| d_i - \sqrt{(x_i - x)^2 + (y_i - y)^2} \right|}{d_i} \quad (11)$$

Where, J is the cost or objective function, k is the anchor node number in communication range of the non-anchor node, d_i is the improved distance information between ith anchor node according to the non-anchor node, x_i is the abscissa of the ith anchor node, y_i is the ordinate of the ith anchor node, x is the abscissa of the pollen and y is the ordinate of the pollen. In the objective function, d_i is subtracted from the distance between pollen and adjacent anchor node of itself. Then, absolute value of the result is divided to d_i to avoid cumulative optimization error. Consequently, global best is acquired by minimizing the value of sum of dependent errors of the every pollen.

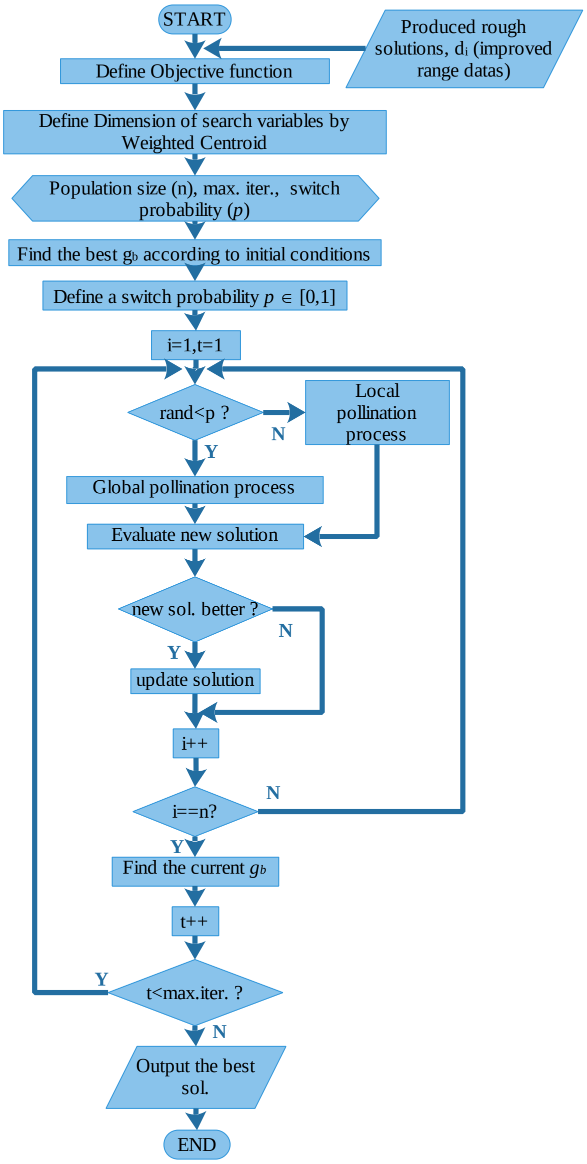

Figure 2. Flower Pollination Algorithm (FPA)

6. Simulations and Results

In simulations, anchor nodes are located edge of the 30x30m square area in equal intervals. Transmitter power of the anchor nodes are assumed to 1mW. Non-anchor nodes are assumed at fixed location and deployed randomly in defined area.

For the channel, path loss attenuation is assumed as fixed (δ=2.7) and previously determined through experimentally. Gaussian noise is assumed as zero mean and standard deviation is 5.

Also, iteration and particle number are selected 20, switching probability is selected 85% for the FPA.

In the light of these assumptions, results are acquired by changing of two parameters. The first parameter is physically intervals of anchor nodes. The second parameter is about number of RSS samples that acquired from the anchor nodes.

Number of RSS samples were selected fixed value as 10 and number of the non-anchor nodes were selected as 20 for the first analysis. Intervals of the anchor nodes were changed respectively 10-15-30m. Under these conditions, simulation results which contain mean-errors are shown below separately and respectively.

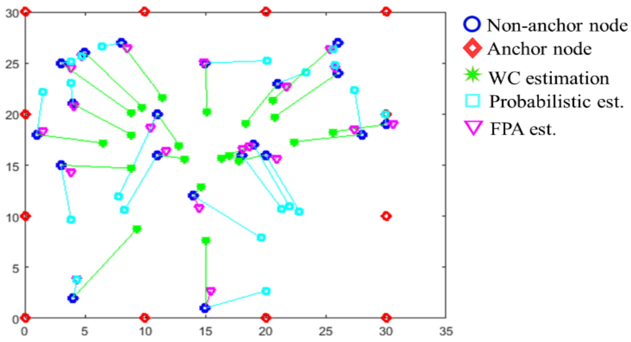

Figure 3. Simulation results for RSS sample=10 and interval=10m

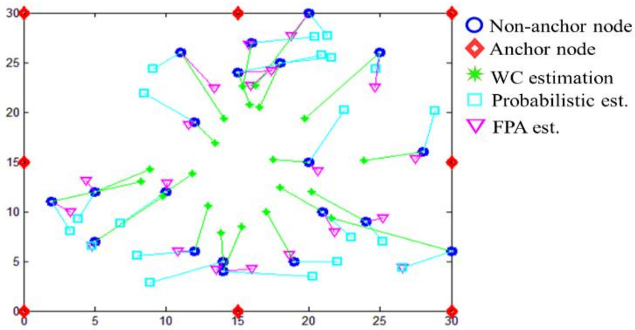

Figure 4. Simulation results for RSS sample=10 and interval=15m

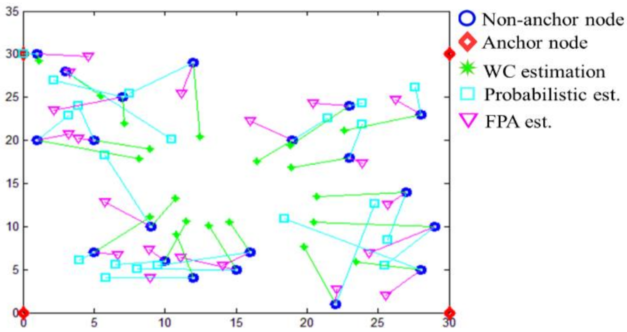

Figure 5. Simulation results for RSS sample=10 and interval=30m

Mean errors for each methods are shown in (Table.1). As can be seen, for each distance interval, FPA localization gives the best results.

Table 1. Results for RSS sample=10

Mean Error[m]	***10***	***15***	***30***
Weighted Centroid	5,424769493	5,064059739	5,135200516
Probabilistic	3,992321645	3,765929552	5,521142680
FPA	1,689722986	1,760534673	2,825703946

In second analysis, number of RSS samples are increased to 50. Simulation results for each distance interval are shown below.

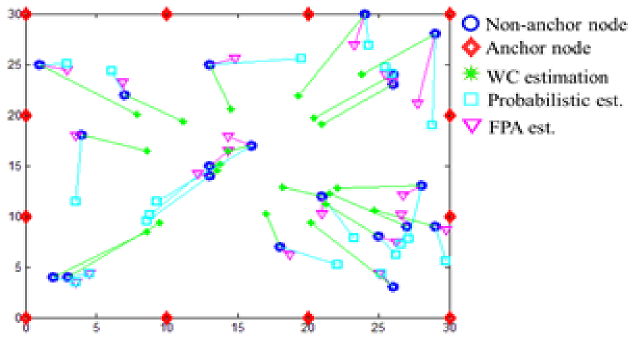

Figure 6. Simulation results for RSS sample=50 and interval=10m

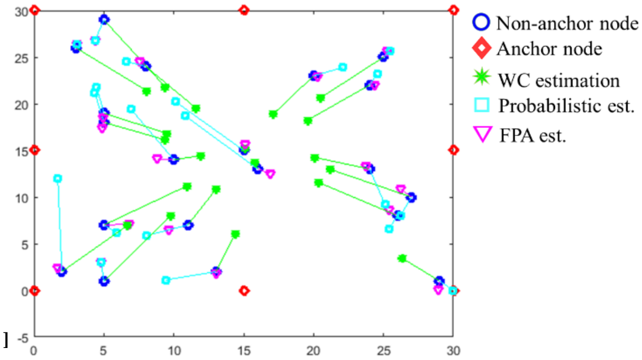

Figure 7. Simulation results for RSS sample=50 and interval=15m

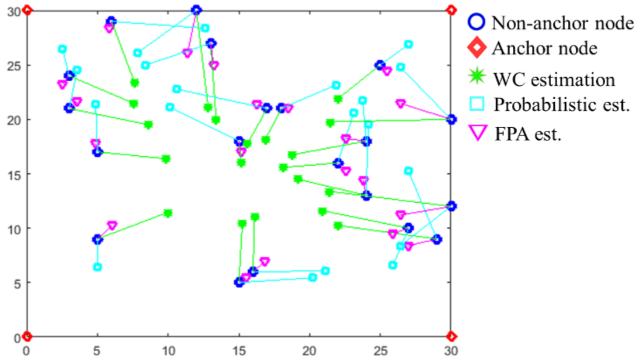

Figure 8. Simulation results for RSS sample=50 and interval=30m

Mean errors for each methods in second analysis are shown in (Table.2). As can be seen, for each distance interval, FPA localization gives the best results. Furthermore increasing of the RSS samples to 50 improved the location accuracy approximately 50% for the FPA.

Table 2. Results for RSS sample=50

Mean Error [m]	***10***	***15***	***30***
Weighted Centroid	5,038320471	5,145930370	5,583851881
Probabilistic	3,845946492	3,252009350	4,824532778
FPA	0,843777095	0,901263359	1,522088241

7. Conclusion

In this study, two different approaches are analysed which used weighted centroid rough results. Both the methods showed improvement according to the weighted centroid localization. When comparison is made between two methods, it shows us that FPA has more accurate results and lower processing load. As a future work, RSSI based location accuracy improvement for mobile nodes will be examined.

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