International Journal of
Applied Mathematics,
Electronics and Computers
ISSN: 2147-8228 http://ijamec.atscience.org

Advanced Technology and Science

Original Research Paper

# Sensor Localization Using Fixed and Dynamic Communication Ranges in Different Types of Distributed Sensor Networks

**Dogan YILDIZ[1], Serap KARAGOL*[1], Prabhat Ranjan PATHAK**

*Accepted 3rd September 2016*

***Abstract:*** Wireless Sensor Network (WSN) refers to a group of locationally dispensed and dedicated sensors for observing and recording the physical conditions of the environment and coordinating the aggregated data at a centrical location. To serve such new applications, localization is largely used in WSNs to define the current location of the sensor nodes. Time of Arrival (ToA) localization is one of the prevalent schemes due to its high estimation accuracy. ToA is a method to estimate the location of a target based on the correlation of the signals and calculating the distances from each anchor to the target by multiplying the speed of light and the time at which the signal is received. In our recent study, we propose Modified 3N algorithm in 2D space. In the Modified 3N algorithm in 2D, three circles were used to localize the target nodes in the network. In this paper; Uniform, Beta, Weibull, Gamma and Generalized Pareto distributed networks are used for localization with the Modified 3N algorithm in 2D and the localization performance of the networks are evaluated and compared using MATLAB simulations. For these simulations, firstly, constant communication range of 10% of the field dimension is used and then dynamic communication ranges that depend on the number of total nodes are used for the same areas.

***Keywords:*** *Wireless Sensor Networks, Localization, Time of Arrival, Statistical Distributions, Modified 3N Algorithm*

## 1. Introduction

In recent years, wireless sensors networks (WSNs) have allured considerable interest in numerous fields including disaster alarm, health, military, environmental, building, car, and mining industries. They also have remarkable potential to ease our daily life activities. The deployment of sensors is based on the fact that sensors are most practical when they are spread in a multitude of numbers, especially for collecting an environmental map of a geographical area such as a rain forest, a complete building, or an agriculture field.

Once the sensors are spread in a sensor application, exact position information is of vital importance [1]. The position of the nodes has a significant role in many fields as routeing, surveillance and monitoring, military, environmental and health applications etc. Localization of a sensor node is fulfilled with the aid of neighboring nodes. The localization can be categorized as known location-based localization, proximity-based localization, angle-based localization, range-based localization and distance-based localization [2].

In this study, we used Time of Arrival Localization (ToA) method which is one of the range-based and distance-based localization techniques. The distance between the two nodes is estimated by measuring the duration of propagation of the signal between the two nodes. This requires clock synchronized nodes, utilizing well-known parameters such as the speed of the signal and the carrier frequency, which is known as the ToA technique. This technique was used in various studies. In [3], each sensor node exploits at least one orthogonal sub-carrier as its assigned marker, to reply the Neighbor Discovery (ND) and ToA estimation requests transmitted by target nodes. The target node utilises the orthogonality throughout sub-carriers to detect the transmitted markers and their corresponding delays [3]. A signal-circle analogy used by Barbeau et al. [4] is generally used analogous to the TOA distance measurement technique. In [5], the authors study the localization of multiple signal sources based on sensors executing time-of-arrival (TOA) measurement in wireless sensor networks. They conceived contemporaneous estimation of source-measurement associations and the source locations, in addition to finding the initiatory signal transmission time. In [6], The authors proposed a localization algorithm that needs no prior information about path loss exponents for non-line-of sight (NLOS) environments. The proposed algorithm evaluates both received-signal-strength (RSS) measurements and time-of-arrival (TOA) measurements. In the proposed localization algorithm the distances calculated with TOA measurements are weighted by the believable factor (BF) obtained from the difference between the estimated distance with TOA measurements and that with RSS ones.

In literature, statistical analysis related to both localization and energy problem in WSNs are available in many studies. Kamyabpour et al. [7] use statistical tools to analyse dependency between WSN parameters and overall energy consumption. In this study, three statistical approaches (linear correlation, non-linear correlation and p-value) are implemented to the consequence of detecting phase to extract the most efficacious parameters on WSN comprehensive energy consumption. The distribution of range estimation error was analyzed by Rasool et. al [8] using both graphical and computational goodness of-fit techniques, which are empirical cumulative distribution function plotting, quantile–quantile plotting, probability density function plotting, kurtosis (K) test, skewness (S) test, linear correlation coefficient (γ) test, Anderson–Darling (A2) test and chi-squared (χ2) test. They proposed a range infiltration algorithm (RFA), which is based on an A2 test and it filters out the range estimates with high errors. In [9], equipped with moments, the optimal fusion rule (OFR) distribution is approximated by Gaussian and Gamma distributions via the moment mapping method. They showed that the Gamma distribution fits the OFR distribution to high extent when compared with Gaussian distribution. Tae Hong et al. [10] proposed a new data filtering schema based on statistical data analysis. Through performance analysis, they show that the

[1] *Electrical and Electronics Engineering Department, Ondokuz Mayis University, 55139, Samsun/Turkey*
* *Corresponding Author: Email: serap.karagol@omu.edu.tr*
*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.*

proposed schema does better than the Kalman filtering schema in terms of the number of messages transmitted. In [11], the authors present the SA-TC algorithm for detecting and thus defending against this serious threat. It is based on the on-demand multi-path routings and uses statistical analysis and time constraint to identify the suspected links. Tsai et al. [12] reported different aspects of a statistical analysis of four representative in-car wireless channels based on the received power data collected from a Binary Phase Shift Keying (BPSK) transmission experiment. They used Rayleigh, Log normal, Nakagami, Rice, and Weibull distributions in their study.

In our previous study, we used a uniformly distributed network to localize the target nodes while a Modified 3N algorithm is being run. But in this paper, we used Uniform, Beta, Weibull, Gamma and Generalized Pareto distributed networks for localization and the localization performance of the networks were evaluated and compared using MATLAB simulations.

## 2. Time of Arrival Based Localization

Time of Arrival (ToA) is a method used to estimate the location of a target node based on the correlation of the signals. This method calculates the distances from each anchor to the target by multiplying the speed of the signal and the time at which the signal is received. This method requires the knowledge of the precise starting time of the transmitted signal and the precise maintenance and synchronization of the clocks at the target and all the anchor nodes is involved.

In general, the field of sensor nodes is sparse in the sense that some nodes may have fewer nodes than neighboring anchors to fully localize. In fact, they may have less than 3 neighbors. A well-known 3 Neighbor algorithm is as follows: Each node that is not equipped with a position-awareness device sends a position request message, a node that knows or can compute its position sends it to all its neighbors, and a node that receives position messages from three different nodes, say $A_1$, $A_2$, and $A_3$, can calculate its position as shown in Fig. 1 (a). However, this algorithm exhibits a deficiency: when a target node receives only two anchor nodes ($A_1$, $A_2$), locations, and two distance measurements, the target node fails to find its own location, due to the obvious ambiguity as shown in Fig. 1(b) [4].

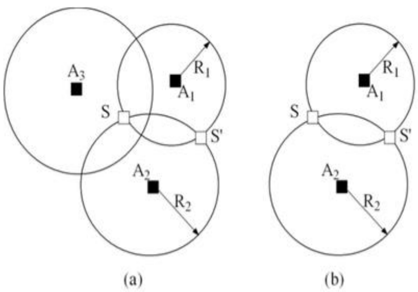


**Figure 1.** (a) three anchors, (b) two anchors

### 2.1. Modified 3N Algorithm in 2D

While the algorithm is being run, the target nodes that are localized are now position-aware and possess the capability to share their positions. This newly found position-aware node is introduced into the pseudo anchor list and the neighboring network is intimated of this change. The gradual increase of the position-aware nodes in the network enable an enhanced localization performance.

**Algorithm 1:** Modified 3N Algorithm in 2D

1. While there are target nodes
   a. `if` maximum number of iterations is exceeded, `stop` (some targets are not located)
   b. `if` less than three anchor nodes are in range, skip this node and `goto` step 1 to consider another target node
   c. `if` there are three or more anchor nodes in range, find the closest three anchor nodes and use them to locate the target node
   d. Add the localized target node into the pseudo-anchor list and remove it from target list
2. `goto` step 1, consider the next in target list.

## 3. Fields in Different Distributions

### 3.1. Uniform Distribution

One of the simplest continuous distributions in all of statistics science is the continuous uniform distribution. This distribution was used for various applications. In [13], A method to obtain a uniform flux distribution with a multi-faceted point focus concentrator for laboratory tests is proposed. The method can be implemented to different types of receiver - photovoltaic or thermal - and no additional device is necessary to homogenise the flux. In [14], a method for evaluating the efficiency level of a Decision Making Units (DMU) when it is in a negatory situation as well as estimating the efficiency using uniform distribution is demonstrated.

This distribution is characterized by a density function that is "flat," and thus the probability is uniform in a closed interval say [A, B]. The density function of the continuous uniform random variable *x* on the interval [A, B] is

$$f(x) = \begin{cases} \frac{1}{B-A} & , \quad A \le x \le B \\ 0 & \quad elsewhere \end{cases} \tag{1}$$

The density function creates a rectangle with base B−A and height 1/B-A. As a result, the uniform distribution is generally called the rectangular distribution [15]-[16]. Note, however, that the interval may not always be closed: [A, B]. It can be (A, B) as well. The density function for a uniform random variable on the interval [1, 3] is shown in Fig. 2.

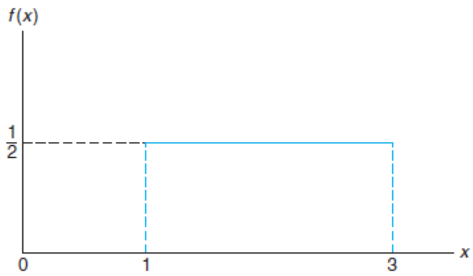


**Figure 2.** The density function for a random variable on the interval [1, 3]

The mean and variance of the uniform distribution [16] are

$$\mu = \frac{A+B}{2} \ \ and\ \sigma^2 = \frac{(B-A)^2}{12} \tag{2}$$

Fig. 3 shows the Uniform distribution of 100 nodes. A heterogeneous node network containing a mix of anchor nodes that have the capabilities of ascertaining their own locations and the target nodes that are non-position-aware is generated as shown in Fig. 3. Blue circle nodes and red square nodes represent position-aware and non-position-aware nodes, respectively.

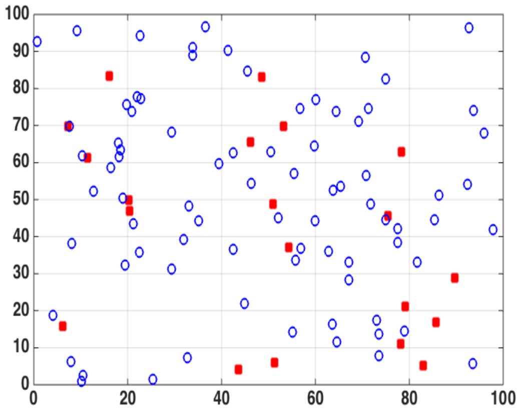


**Figure 3.** Uniform distribution of 100 nodes

### 3.2. Beta Distribution

A beta function is defined by

$$B(\alpha,\beta) = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}dx \qquad (3)$$

$$= \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}, \quad for\ \alpha,\beta > 0$$

where $\Gamma(\alpha)$ is the gamma function.

The continuous random variable $x$ has a beta distribution with parameters $\alpha > 0$ and $\beta > 0$ if its density function is given by

$$f(x) = \begin{cases} \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1} \ , & 0 \le x \le 1 \\ 0\ , & elsewhere \end{cases} \qquad (4)$$

Note that the uniform distribution on (0, 1) is a beta distribution with parameters $\alpha = 1$ and $\beta = 1$.

The mean and variance of a beta distribution with parameters $\alpha$ and $\beta$ are

$$\mu = \frac{\alpha}{\alpha+\beta} \quad \text{and} \quad \sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \qquad (5)$$

respectively [15].

The beta distribution is a probability distribution described in an interval [0 1], parameterized by two shape parameters α and β. The beta distribution has an advance over other probability distributions in that its domain is bounded and it procures various shapes depending on its parameters: flat, convex, concave and slanted. When α=β, the distribution is symmetric about $x$ = ½ [16]. Fig. 4. shows Beta distribution of 100 nodes. Two parameters of Beta function, α and β, are choosen as 4 and 2 respectively. Asymmetric distributions are obtained by choosing alpha and beta to be different.

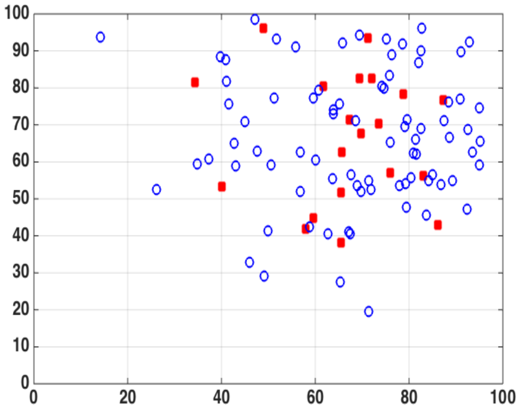


**Figure 4.** Beta distribution of 100 nodes

### 3.3. Weibull distribution

Modern technology has enabled engineers to design many sophisticated systems whose process and safety depend on the reliability of the several components making up the systems. For example, a steel column may buckle, a fuse may burn out, or a heat-sensing device may fail. Alike components subjected to alike environmental situations will fail at different and imponderable times [17]. The Weibull distribution which was proposed by Waloddi Weibull in 1939 is a very important time of life distribution and is extensively used in many fields [18]. For example,Weibull Statistical Distribution is a prevalent method for examining wind speed measurements and specifying wind energy potential. Weibull probability density function can be used to predict wind density, wind energy potential and wind speed [19]-[20].

The continuous random variable $x$ has a Weibull distribution, with parameters α and β, if its density function is given by

$$f(x) = \begin{cases} \alpha\beta x^{\beta-1} e^{-\alpha x^{\beta}} \ , & x > 0 \\ 0\ , & elsewhere \end{cases} \qquad (6)$$

where $\alpha > 0$ and $\beta > 0$.

The graphs of the Weibull distribution for α = 1 and various values of the parameter β are illustrated in Fig. 5. It can be seen from the figure that the curves change highly in shape for different values of the parameter β. If β = 1 taken, the Weibull distribution changes to the exponential distribution. For values of β > 1, the curves become somewhat bell shaped and look like the normal curve but display some curvature.

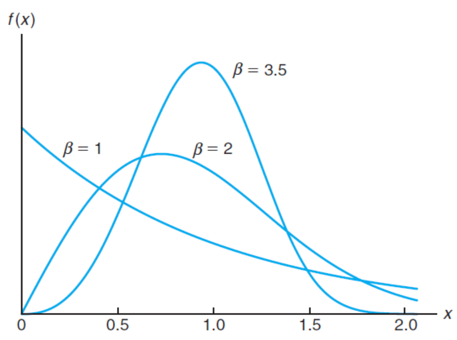


**Figure 5.** Weibull distributions (α = 1)

The mean and variance of the Weibull distribution are

$$\mu = \alpha^{-\frac{1}{\beta}}\Gamma(1+\tfrac{1}{\beta}) \quad (7)$$

$$\sigma^2 = \alpha^{-\frac{2}{\beta}}\left\{\Gamma\left(1+\tfrac{2}{\beta}\right) - \left[\Gamma(1+\tfrac{1}{\beta})\right]^2\right\}$$

Fig. 6 shows Weibull distribution of 100 nodes. This distribution has two parameters which k > 0 is the shape parameter and λ > 0 is the scale parameter of the distribution. k and λ are chosen as 1 and 0.12 respectively for this simulation.

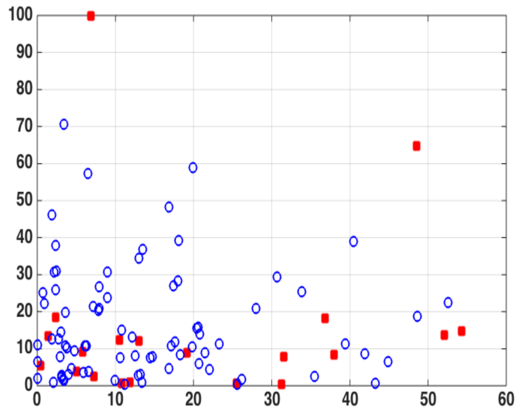


**Figure 6.** Weibull distribution of 100 nodes

### 3.4. Gamma Distribution

The gamma distribution derives its name from the well-known gamma function, studied in many areas of mathematics. The gamma function is defined by

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx, \quad \text{for } \alpha > 0 \quad (8)$$

The continuous random variable $x$ has a gamma distribution, with parameters α and β, if its density function is given by

$$f(x) = \begin{cases} \frac{1}{\beta\alpha\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}, & x > 0 \\ 0, & \text{elsewhere} \end{cases} \quad (9)$$

where α>0 and β>0 [17], [21].
Graphs of several gamma distributions are shown in Fig. 7 for certain determined values of the parameters α and β. The special gamma distribution for which α = 1 is called the exponential distribution [17].

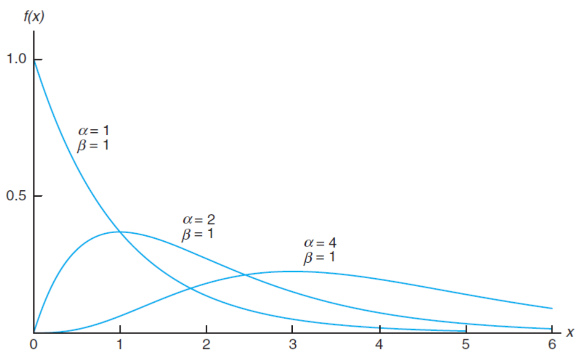


**Figure 7.** Gamma distributions

Fig. 8 shows Gamma distribution of 100 nodes. This distribution has two parameters α and β, they are chosen as 0.15 and 0.4 respectively for this simulation.

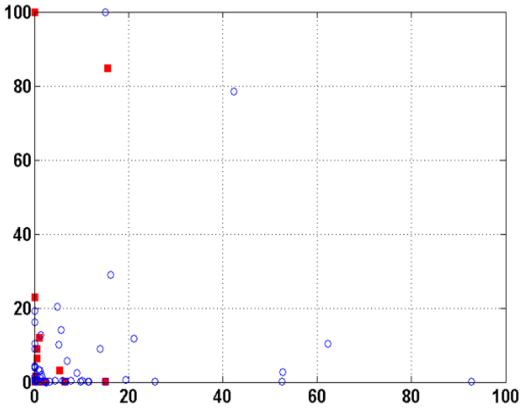


**Figure 8.** Gamma distribution of 100 nodes

### 3.5. Generalized Pareto Distribution

The Generalized Pareto distribution introduced by

$$F(q) = 1 - e^{-\frac{q-q0}{\alpha}}, \quad \kappa = 0 \quad (10)$$

$$F(q) = 1 - \left(1 - \kappa\frac{q-q0}{\alpha}\right)^{1/\kappa}, \quad \kappa \neq 0 \quad (11)$$

where $\alpha$ is the scale parameter, $\kappa$ is the shape parameter, and $q_0$ is the threshold [22].

Fig. 9. shows Pareto distribution of 100 nodes. Three parameters of Pareto function, tail index (shape, $\kappa$), scale parameter $\alpha$ and threshold (location) parameter $q_0$, are chosen as 0.1, 0.1 and 1 respectively. When $\kappa$>0 and theta is equal to $\alpha/\kappa$ the Generalized Pareto is equivalent to the Pareto distribution.

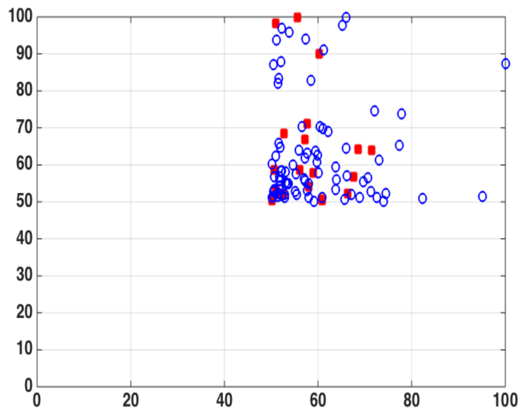


**Figure 9.** Pareto distribution of 100 nodes

## 4. Analysis of Time of Arrival Simulations

### 4.1. Design of Simulation Environment

The simulation environment is designed for the quantitative performance study of the proposed modified 3N algorithm in 2D. For simplicity and ease of presentation, we limit the environment to 2 dimensions, but the Modified 3N algorithm is capable of operating in 3D. A pseudo-anchor list is created that serves as a dynamic anchor list while the simulation is being run. As the new target nodes are localized, they are added to the list of pseudo-anchors, and the whole network is made aware of these newly localized nodes for the purpose of enhancing the performance of localizing other target nodes with the help of this new knowledge. The simulation creates a distance matrix that is generated using the Euclidean method of calculation of the distance between the anchor nodes. The connectivity of the nodes in the network (i.e., the average number of neighbors) is an important parameter that has a strong impact on the accuracy of most localization algorithms. This forms the basis for the generation of other modules needed, such as adjacency lists. This list of the nodes is in the communication range of that particular target node. From this adjacency list, each target node determines its neighbors. An approximated circle is constructed, using the distance from the anchor node to the target node as the radius and the absolute position of the anchor as the center. The intersection of circles gives a location estimate of the target node.

### 4.2. Simulation Results for 2D

In this section, the localization capability of the ToA based localization algorithm is presented with exhaustive Monte-Carlo simulations, and the effect of the input parameters determining the self-localization environment for Modified 3N algorithm in 2D is also presented. The simulation environment to test the performance of the algorithm on all combinations of the context parameters is formulated. Each Monte-Carlo simulation is generated for a particular set of input parameters and run 100 times with different fields and with randomly located nodes. The results are then averaged. The input parameters are the percentage of anchor nodes (position-aware and initially synchronized nodes), the number of target nodes, and the range of communication. The number of nodes varying from 50 to 400 and they are deployed in a square field dimension of 100x100 units. In some application scenarios, nodes may be mobile. In this paper, however, we focus on static networks, where nodes do not move, since this is already a challenging condition for distributed localization

Fig. 10 is produced by varying the percentage of anchor nodes from 10% to 35% for a constant communication range of 10% of the field dimension for uniform distribution. X-axis is the number of nodes and y-axis is the percentage of target nodes localized. Modified 3N algorithm is run on Pareto, Weibull and Beta distributed environments as shown in Fig 11, Fig. 12 and Fig 13 respectively. The results show that uniform distributed environment is quite sensitive to the change of node numbers. Increasing number of anchor nodes does not change significantly on Weibull, Pareto and Beta distributed environments. Among all distributions, Pareto distribution shows the best results.

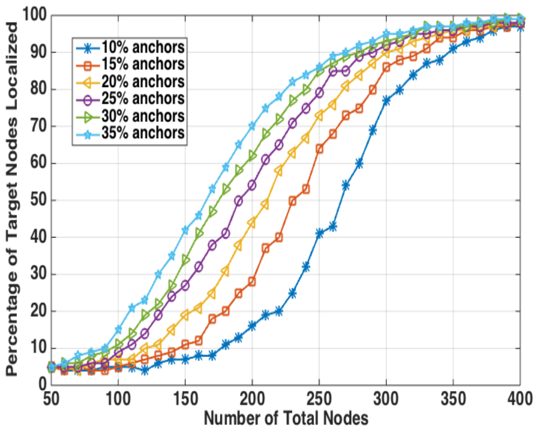


**Figure 10.**Percentage of target nodes localization for uniform distribution

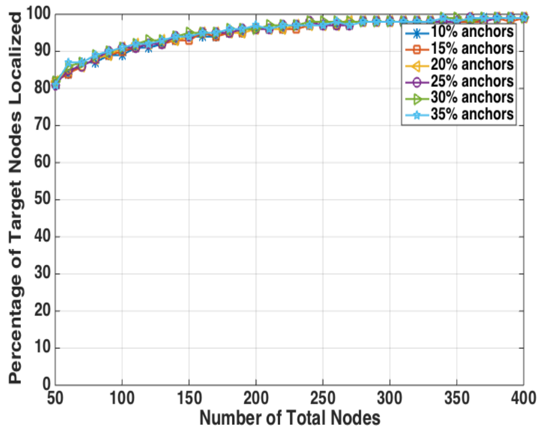


**Figure 11.** Percentage of target nodes localization for Pareto distribution

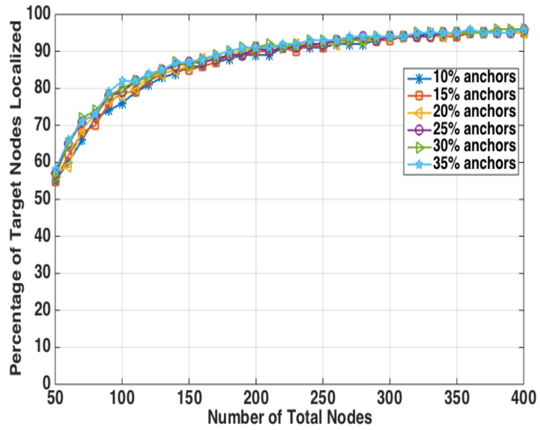


**Figure 12.**Percentage of target nodes localization for Weibull distribution

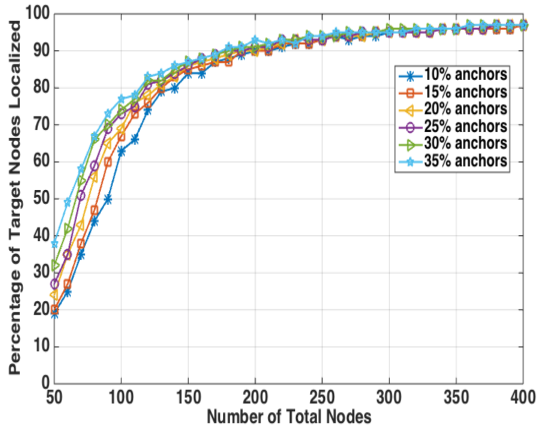


**Figure 13.** Percentage of target nodes localization for beta distribution

Fig. 14, Fig.15 and Fig. 16 show the comparison of four distributed environments with different number of anchor nodes. Among all distributions, localization of Pareto distributed nodes shows the best result for all simulations.

 

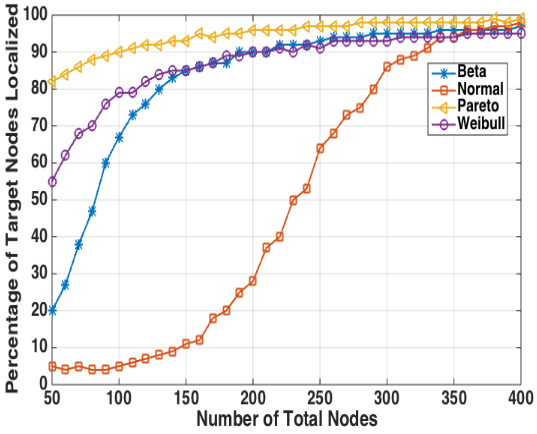


**Figure 14**. The number of anchor nodes = 15 %

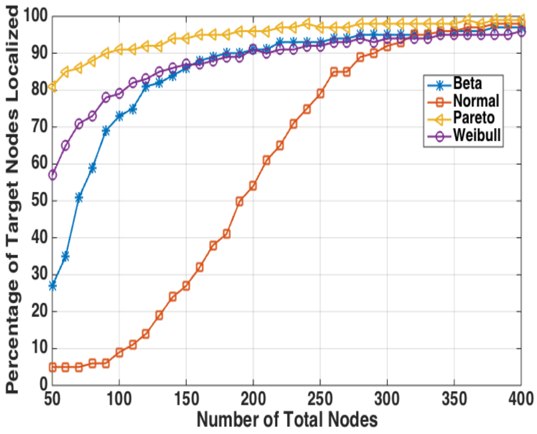


**Figure 15.** The number of Anchor nodes = 25 %

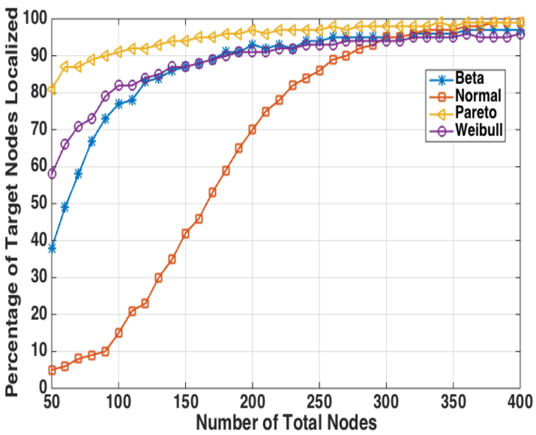


**Figure 16.** The number of Anchor nodes = 35 %

For other simulations, dynamic ranges is used to localize the unknown nodes. Extensive simulations are conducted in an environment similar to the one created by Barbeau and Kranakis [4]. The sensors are spread in a unit square independently with uniform, beta, gamma, weibull and generalized pareto distributions respectively. The reachability range of each node is as, given by the Eq. (12).

$$r = \sqrt{\frac{\log n + k \log \log n + \log(k!) + c}{n\pi}} \quad (12)$$

The constants k and c are given a value of 1 and n is the number of deployed nodes in the network.

Fig. 17 is produced by varying the number of total nodes from 50 to 400 for a dynamic communication range that depends on the number of total nodes for these distributions. X-axis is the number of nodes and y-axis is the percentage of target nodes localized. Modified 3N algorithm is run on Uniform, Beta, Weibull, Gamma and Pareto distributed environments as shown in Fig. 17, Fig. 18, Fig. 19, Fig. 20, Fig. 21 and Fig. 22 for different percentage of anchor nodes. Generally, for all of the distributions, Modified 3N algorithm has better results in the Generalized Pareto distributed fields than in the other four distributed fields. With the increasing number of nodes, the localization performance of Modified 3N algorithm generally increases for uniform distribution. And with the increasing number of nodes, the localization performance of Modified 3N algorithm initially increases and then changes around nearly a fixed value for other distributions. The reason for this result is when the number of nodes increases, the range get smaller according to Eq. (12).

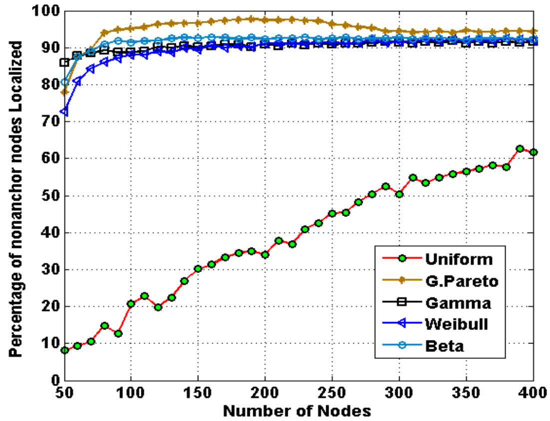


**Figure 17.** The number of anchor nodes = 10 % for dynamic range

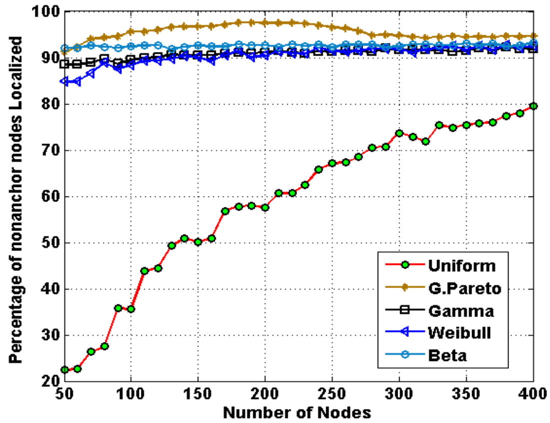


**Figure 18.** The number of anchor nodes = 15 % for dynamic range

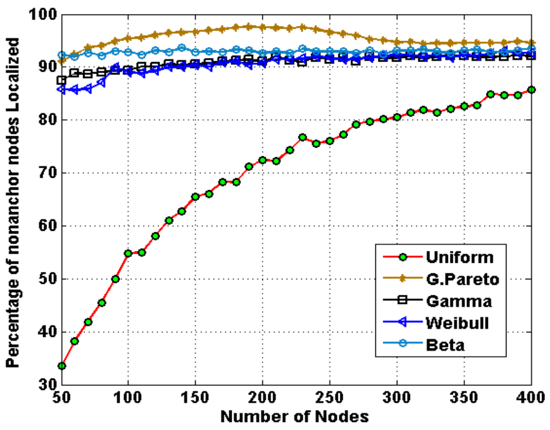


**Figure 19.** The number of anchor nodes = 20 % for dynamic range

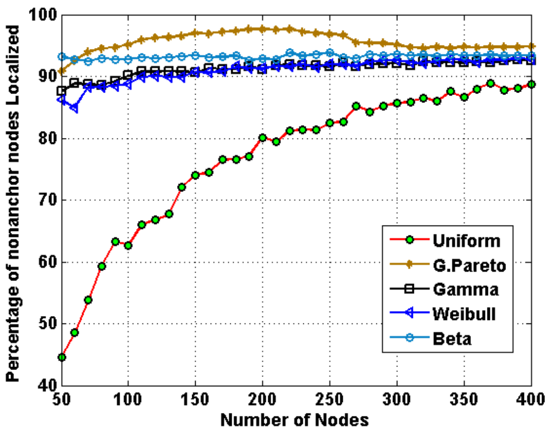


**Figure 20.** The number of anchor nodes = 25 % for dynamic range

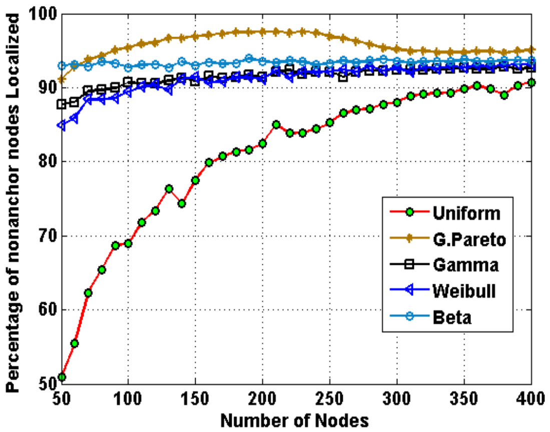


**Figure 21.** The number of anchor nodes = 30 % for dynamic range

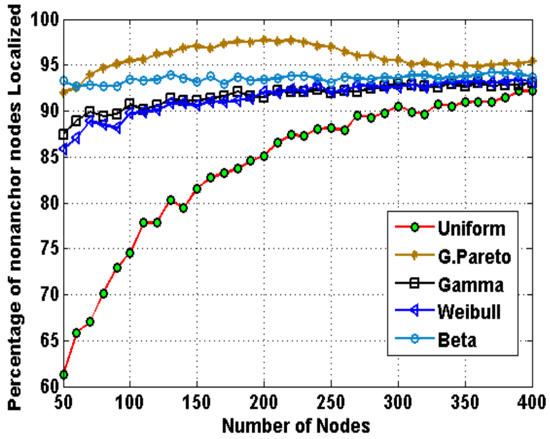


**Figure 22.** The number of anchor nodes = 35 % for dynamic range

## 5. Conclusion

Two-dimensional localization in wireless sensor networks have been widely studied in literature. In this paper, the Modified 3N algorithm in 2D is introduced and this algorithm was tested on an environment created with Uniform, Weibull, Generalized Pareto, Gamma and Beta distributions. With the increasing number of nodes, the localization performance of Modified 3N algorithm generally increases for uniform distribution. The localization performance of Modified 3N algorithm initially increases and then changes around nearly a fixed value for other distributions with the increasing number of nodes.

For all environments, the simulations conducted have shown that the introduction of the knowledge of newly localized nodes into the network enhances its localization capability. If the nodes cannot be located by the 3N algorithm because of the limitations on range and sparsity of the anchors, then those nodes will also not be localized by the modified algorithm. The sensors that detect the movements of the objects are not considered in this paper. They will be addressed in our future work.

## References


[1] Romer K., Mattern F. The design space of wireless sensor networks, IEEE Wirel. Commun., Vol. 11, Issue 6, 2004, pp. 54–61.

[2] Kuriakose J., Joshi S and George V.I. Localization in Wireless Sensor Networks: A Survey, CSIR Sponsored X Control Instrumentation System Conference (CISCON-2013), pp.73-75, 2013, India, Tamilnadu.

[3] Jamalabdollahi M., Zekavat S. A. R. Joint Neighbor Discovery and Time of Arrival Estimation in Wireless Sensor Networks via OFDMA, IEEE Sensors Journal, Vol. 15, Number 10, 2015, pp. 5821-5833.

[4] Barbeau M., Kranakis E., Krizanc D., Morin P. Improving Distance Based Geographic Location Techniques in Sensor Networks, 3rd International Conference on Ad-Hoc Networks &Wireless, 22-24 July 2004, Canada, Vancouver, British Columbia.

[5] Shen H., Ding Z., Dasgupta S., Zhao C. Multiple Source Localization in Wireless Sensor Networks Based on Time of Arrival Measurement, IEEE Transactions on Signal Processing, Vol. 62, Issue 8, 2014, pp. 1938-1949.

[6] Mogi T., Ohtsuki T. TOA Localization using RSS Weight with Path Loss exponents Estimation in NLOS


 

Environments, Proceedings of 14th Asia Pasific Conference (APCC2008), 14-16 October 2008, Japan, Tokyo.
[7] Kamyabpour N., Hoang D. B. Statistical Analysis to Extract Effective Parameters on Overall Energy Consumption of Wireless Sensor Network (WSN), IEEE 13th International Conference on Parallel and Distributed Computing, Applications and Technologies, 14-16 December 2012, China, Beijing.
[8] Rasool I., Kemp A. H. Statistical analysis of wireless sensor network Gaussian range estimation errors, IET Wireless Sensor Systems, Vol. 3, Issue 1, 2013, pp. 57–68.
[9] Aldalahmeh S., Ghogho M. Statistical Analysis of Optimal Distributed Detection Fusion Rule in Wireless Sensor Networks, Wireless Advanced (WiAd) Published by IEEE, 25-27 June 2012, United Kingdom, London.
[10] Hong S. T., Chang J. W. A New Data Filtering Scheme Based on Statistical Data Analysis for Monitoring Systems in Wireless Sensor Networks, IEEE International Conference on High Performance Computing and Communications, 2-4 September 2011, Canada, Banff.
[11] Zhao Z., Wei B., Dong X., Yao L., Gao F. Detecting Wormhole Attacks in Wireless Sensor Networks with Statistical Analysis, WASE International Conference on Information Engineering, 14-15 August 2010, China, Beidaihe.
[12] Tsai H. M., Viriyasitavat W., Tonguz O. K., Saraydar C., Talty T., Macdonald A. Feasibility of In-car Wireless Sensor Networks: A Statistical Evaluation, 2007 4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks, 18-21 June 2007, USA, California, San-Diego.
[13] R. P. Enciso R. P., Gallo A., Rosas D. R., Vidal E. F., Rabaga C. P. A simple method to achieve a uniform flux distribution in a multi-faceted point focus generator, ELSEVIER, Renewable Energy Journal, Vol. 93, 2016, pp. 115-124.
[14] Hossain Md. K., Kamil A. A., Mustafa A. , Baten Md. A. Estimating DEA Efficiency Using Uniform Distribution, Bulletin of the Malaysian Mathematical Sciences Society, Vol. 37 Number 4, 2014, pp. 1075-1083.
[15] Forbes C., Evans M., Hastings N., Peacock B. Statistical Distributions, John Wiley&Sons, Inc., Publication, fourth Edition, New Jersey ,2011.
[16] Park S. Y., Lee J. J., Stochastic Opposition-Based Learning Using a Beta Distribution in Differential Evolution, IEEE Transactions On Cybernetics, Vol. 46, Number 10, October 2016, pp.2184-2194.
[17] Walpole R. E., Myers R. H., Myers S. L., Ye K. Probability & Statistics for Engineers & Scientists, Ninth Edition, Prentice Hall, Boston, USA,2012.
[18] He B., Cui W., Du X. An additive modified Weibull distribution, ELSEVIER Reliability Enginnering & System Safety Journal, Vol.145, 2016, pp. 28-37.
[19] Mohammadi K., Alavi O., Mostafaeipour A., Goudarzi N., Jalilvand M. Assessing different parameters estimation methods of Weibull distribution to compute wind power density, ELSEVIER Energy Conversion and Management Journal, Vol.108, 2016, pp. 322-335.
[20] Usta I. An innovative estimation method regarding Weibull parameters for wind energy applications, ELSEVIER Energy Journal, Vol. 106, 2016, pp. 301-314.
[21] Clarke B. R., McKinnon P. L., Riley G. A fast robust method for fitting gamma distributions, Springer Regular Article, , Vol. 53, Issue 4, Nov 2012, pp. 1001-1014.
[22] Bhunya P.K., Berndtsson R., Jain S. K., Kumar R. Flood analysis using negative binomial and Generalized Pareto models in partial duration series (PDS), ELSEVIER Journal of Hydrology, Vol. 497, 2013, pp. 121–132.