Journal of Engineering and Applied Sciences 13 (2): 406-414, 2018
ISSN: 1816-949X

An Efficient Localization based on Relevance Vector Machine with Glow-Worm Swarm Optimization for Wireless Sensor Networks

M. Arun and P. Manimegalai
Department of Electronics and Communication Engineering, Karpagam University, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India

Abstract: Wireless Sensor Networks (WSNs) have the prospect to become the most crucial technology of the future. Based on the applications, there is a need to locate the physical location of sensor node to improve the performance. This is known as localization problem. Some traditional localization algorithms are used but still convergence problem exists. So, to solve the above problems and obtain an efficient location identification, a system has been designed using machine learning and swarm intelligence. In this research, a Relevance Vector Machine (RVM) with Glow-worm Swarm behaviour based optimization Algorithm (GSA) is proposed for efficient localization. Here, the trilateration, triangulation and Maximum Likelihood (ML) based location discovery process is focused. For high accurate localization, the proposed system considers the node density factor. In this process, the node is in the overlapping region of circles considered as trilateration problem and it is solved by RVM. The RVM is mainly used for splitting the anchor and overlapping region node and similarly to find the weight for those nodes, so that, the processing time is reduced. After finding the innermost intersection of a point, the GSA is used to update the archive based on the distance and geometric topology constraints. The evaluation of proposed RVM-GSA localization is compared with Average Weight Based Centroid Localization (AWBCL) algorithm with the help of MATLAB tool. The obtained result shows that the proposed RVM-GSA algorithm is a promising scheme that can minimize the localization problem.

Key words: Wireless sensor networks, localization, trilateration, triangulation, maximum likelihood, relevance vector machine, Glow-worm swarm behaviour based optimization algorithm

INTRODUCTION

In the recent technology development, the wireless network occupies a vast area. Due to the significant improvement, there is a need for safe and secure communication. Hence, many researchers opted for sensor network research but still there is a necessity to build an effective network. While entering into the sensor network applications such as environmental monitoring, inventory management, intrusion detection, etc., the problem is identified, the sensing data is transferred and controlled by many controlling units like base station, since without knowing the sensor location this process is meaningless. Hence, localization is considered here as an important factor. It decides the parameters such as scalability, design cost and lifetime of a network. A statement made by Alrajeh is that the location of the collected data is important. They developed sensor node architecture and its applications with various localization techniques.

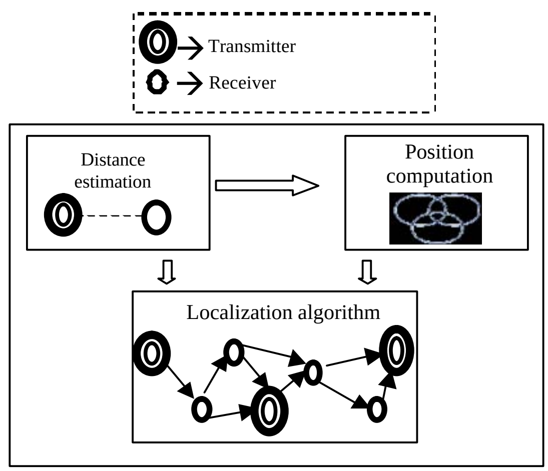

Fig. 1: Localization components

The representation of localization model is shown in Fig. 1. It contains distance estimation as a separate component and position computation as an another part,

Corresponding Author: M. Arun, Department of Electronics and Communication Engineering, Karpagam University, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India

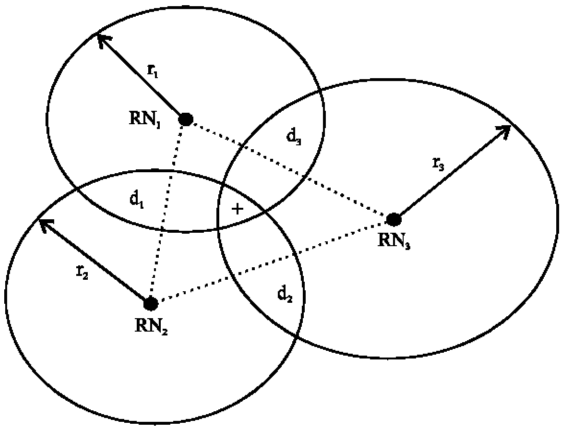

Fig. 2: Example for tri-lateration representation

and finally, these units are controlled by the localization algorithms. The position estimation between two nodes is denoted as distance or angle estimation. Next, if a data is received by a node, then it is computed based on the nodes and anchor nodes position. To process and compute all other nodes in a network is managed by the localization. In network architecture, if a node cannot determine its current location, then it is called as an unknown node. If a node's location is recognized by any other positioning hardware then the node is said to be an Anchor or Beacon node. Hence, Beacon node is kept as a reference point to estimate the coordinates of other unknown nodes.

The localization problem is one of the multi-objective processes because sensor networks may be affected by many ways such as trilateration, lateration, angulation, etc. To solve such issues it is necessary to consider the effective algorithm. Recently, Ali made a Differential Evolution (DE) based algorithm for solving multi-objective optimization problems. Now a days, the Evolutionary Algorithm (EA) plays a major role in problem identification and it also provides some solutions to that complex problem.

It is estimated by the communication difference between localized node and unlocalized node to determine the exact geometrical position. Exactly, it is made with the distance and angle between the nodes. Some concepts are considered here for an evaluation. The term "Lateration" occurs if the distance between nodes is measured to estimate location. If the angle between nodes is considered for estimation, then it is termed as "Angulation". The next important factor is "Trilateration" which is a process of measuring the distance from three nodes to estimate the location of node. As shown in Fig. 2, the intersection of three circles is calculated and that determines a single point which is a position of unlocalized node. The RN_1-RN_3 represent the Reference Node (RN) which is selected based on the formation of triangle by the nodes. This process is made if it satisfies the following condition:

$$d_1 > d_2 > d_3,\ d_1 > d_2 > d_3 \quad (1)$$

Where:
d_i = The mutual distances between two reference nodes
r_i = The radius of the circle where i = 1, 2, 3

The next concept used for localization is Triangulation; it is a process of establishing the distance between any two points. It is made by observing the nearest RN to merge the process. The triangle follows the different sides and permits the size of the angles in the triangle. It is measured with atleast two angles of an un-localized node from two localized nodes to estimate its position. Youssef and Youssef (2007) state the sine and cosine used for estimating the node's position. Apart from these processes, the multi-lateration concepts of more than three nodes are used in location estimation.

The next key element is Maximum Likelihood (ML) which is the type of estimation initiated by Johann and Hamboker (1994). Many researchers earlier focused on this estimation and obtained some refinement. In sensor network there is a need for record about the data collection and the location must be stamped for future reference. Hence, this estimation derives from triangulation and considers the imperfect distance measurements.

The main contribution of this research is to discover the location based on the localization concept with trilateration, triangulation and Maximum Likelihood (ML). In the first part of the research, the relevance vector machine is used to construct the location distance modules for the sensor nodes deployed in the hostile environment, it is based on node density. These processes are further computed for calculating the location of individual sensor nodes. Secondly, the processing time is reduced by finding the weight of the node and splitting the anchor/overlapping region node with the help of RVM. Finally, the Glow-worm Swarm Behaviour based Optimization Algorithm (GSA) is applied to achieve the information with respect to geometric topology constraints. This approach reduces the localization-communication cost at individual sensor nodes and increases the lifetime of the entire network. It improves the localization coverage.

Literature review: To deal with the localization problem, Meng presented an efficient Expectation-Maximization (EM) algorithm for Maximum Likelihood (ML)

Table 1: Summary of localization algorithms

Citation	Description	Algorithms	Types	Merit/Complexity
Morelande *et al*. (2008)	Bayesian node localisation in wireless sensor networks	Bayesian belief networks	Distributed	It is capable of accurately localising a large number of nodes and complexity is low
Liu *et al*. (2015)	Detecting selective forwarding attacks	Per-Hop Acknowledgement (PHACK)	Centralized	It uses lightweight detection algorithm based only on the neighbourhood information Accuracy is improved and overhead is reduced
Branch *et al*. (2013)	Network outlier detection in wireless sensor networks	k-Nearest Neighbors (k-NN)	Distributed	It dynamically updates the data and detects the node failure. Complexity is moderate
Lee *et al*. (2013)	Novel range-free localization	Multidimensional Support Vector Regression (MSVR)	Isotropic and anisotropic networks	It uses second-order cone programming and trained by convex optimization
Shao *et al*. (2014)	The triangulation and Maximum Likelihood (ML) estimator for Angle of Arrival (AOA) based self-localization	Efficient closed-form AOA based self-localization algorithms	Centralized	The cramer-Rao Lower Bound (CRLB) is used for ML estimation. Finally, the tangent instability is avoided by Autonomous Coordinate Rotation (ACR) method
Das and Ram (2016)	Detect faulty nodes	Range-free localization algorithm (DV Hop)	Distributed	Localization accuracy is improved but hardware requirement is needed. Hardware cost may get varies

estimation. Initially, they made energy sensor decomposition for each sensor node to superimpose the energy signals from multiple sources. After completing the decomposition process, they made an evaluation based on energy, decay factor and location parameter. The Sequential Dominant Source (SDS) initialization model and an incremental parameterized search refinement scheme are introduced here to boost the algorithm and maximize the accuracy. The Cramer-Rao Lower Bound (CRLB) is considered here for theoretical evaluation to verify the functionality of their method. Finally, the comparison results are made with multi-resolution search, exhaustive search, CRLB and their proposed EM algorithm. The statement which is made by them is that the EM scheme has lower computation complexity when comparing with traditional schemes. Finally, they suggested studying and designing a new distributed algorithm for multisource localization.

Tran and Nguyen (2008) made a research on the problem of estimating the geographic locations of nodes. They proposed an Localized Support Vector Machine (LSVM) by concentrating on the connectivity issues present in the non-self positioning network. The process is initialized based on the hop counts and it depends on traditional Super Vector Machine (SVM) learning. They proved that SVM is not only for classification but it is also applicable for localization problem. Finally, they addressed the coverage-hole problems and border problems effectively. After completing all the above process, the mass spring optimization is merged with Localized Support Vector Machine (LSVM) to improve the location estimation.

In some traditional localization algorithms, the distance measure error is not considered and hence the performance is degraded because of this location error rate. These limitations occur due to the order mismatch between hops and distance. Hence, to overcome this issue, Tang *et al*. (2016) coined an algorithm called Support Vector Machine based Range-free localization (RFSVM) algorithm. The relationship between hops and distance is managed by introducing the new matrix called as transmit matrix. The remaining unknown nodes position is estimated with the help of SVM.

The main objective of any localization based research is that, it must learn the model that provides the mapping function between sensor measurements and location of the target. In Received Signal Strength Indicator (RSSI) based noisy environment the sufficient labelled data is needed for training. With increasing demand the algorithm should be capable of updating the learning model. Hence, Yoo and Kim (2015) reviewed some traditional models based on semi-supervised learning or online learning for the localization. They modelled 13 static sensor nodes that are fixed with the 3×4 m workspace. They tuned semi-supervised learning framework from classification problem to a regression problem. The evaluation is made with the circular trajectory which is used for tracking the nodes. Finally, they combined manifold regularization framework with supervised online SVR and named it as online semi-supervised regression algorithm. Table 1 presents a summary to understand the previous algorithms used for localization problems.

The difficulty faced by the localization is dynamic tracking. For example, if we need to track the user, then there is a need for signal transmitter or any access point. Pan *et al*. (2012) tracked the mobile users with the help of semi-Supervised Co-localization. It is based on the machine learning-based approach for tracking mobile users. They performed both labelled and unlabelled data for offline training phase and then for online phase the weighted k-nearest-neighbor method is used to localize a mobile client. Boukerche *et al*. (2007) made a detail representation about the localization systems. Nguyen *et al*. (2015) proposed a maximum likelihood based localization in multi-hop network and it is termed as kHopLoc. For Monte Carlo training phase it uses the algorithm to generate the multi-hop connection probability density functions. It is also utilized to build the likelihood functions to achieve the node's location. Many range-free algorithms are made with the GPS to improve the localization WSNs. They also suggested some points to work it out on non-uniform node deployments.

Simonetto and Leus (2014) analysed distributed maximum likelihood network localization. Initially, they formulated the problem, relaxing it in maximum likelihood. The relaxations depend upon the Probability Density Function (PDF) of the noise. They derived a computational efficient edge-based version of ML convex relaxation class. The distributed algorithm is designed to solve the edge-based convex programs with the help of nearest nodes.

Salman *et al.* (2014) made an optimization in localization. The energy constraints are considered here to manage the computational power by concentrating on Received Signal Strength (RSS)-based localization. The main advantage of selecting the RSS is that it does not require any additional hardware and power. To provide the low complexity solution they made an improvement in Linear Least Squares (LLS) method and named it as the Weighted Least Squares (WLS). Additionally, the reference anchor optimization is made to reduce the Mean Square Error (MSE).

Problem statement: From the literature review, it is noticed that most of the researchers focused on the concept of localization to determine the position. As mentioned earlier, localization may be made on known and unknown positions of nodes and it may be relative or absolute. Most of the works were made in range-based localization to maintain the accuracy level. Since, the main limitations of the existing methods are localization, problem is unavoidable while entering into the real time applications in WSNs. In some cases, the problems are identified in the edges of the deployment area; it means that the localization accuracy of each node is less at the edges of the deployment area but accuracy is improved for those nodes located in the middle of the deployment region. The merit of selecting the SVM algorithm is that, it assumes every node that can measure direct signal strength from all the beacons. Hence, to improve the accuracy the modification is made in SVM and named it as Localized Support Vector Machine (LSVM). But still it is suitable only for moderate networks. For complex wide networks LSVM is not applicable because while transmitting the signals from a small subset of beacons, the location is not predicted. So, this technique would be significantly less accurate. The previous research AWBCL algorithm is considered here for an evaluation.

MATERIALS AND METHODS

The proposed research follows support vector machine and enhances some features in Glow-swarm optimization algorithm for network adaptation. This section presents algorithmic and implementation model in terms of localization.

Support vector machine: Initially, the support vector machine is discussed to initiate the localization process. Cortes and Vapnik (1995) invented this SVM for classification. As discussed earlier, the SVM is a good decision tree learning algorithm that may follow proper rule learning and assign labels to each object. This method is selected because it behaves similar to the human brain. The ideal representation is to maximize the mathematical function based on the set of data not on equation. As per the Abe (2015) statement, SVM is one of the structural risk minimization techniques. However, it may solve both linear and nonlinear classification. In non linear case, the mapping is made in terms of high dimensional feature space. In sensor networks, the nodes are distributed randomly or sometimes it may be centralized. Hence, instead of training data network details collected, it may be large in dimension and infinite. To overcome the limitation of high dimension, the SVM initiates the kernel function.

Let us consider the 'm' sensor nodes in a certain area for measurement. The main objective is to make localization by maximizing the distribution to improve the performance. The training set is represented as $S=\{(x_i, y_i)\}_{i=1}^{n}$. Where, training data $\{x_i\}$ is separated into two types with the vector representation 'w' and 'b'. It is denoted as hyper plane {w, b}. To get proper plane, Eq. 2 must be solved:

$$\min_{w,\xi}\Phi(w,\xi)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\xi_i \quad (2)$$

Where:

w = Coefficient vector
Φ = An N×M design matrix
ξ_i = Slack variables
C = The parameter which is selected by the user while optimizing the problem

$$y_i(w.x_i+b)\geq 1-\xi_i \text{ and } \xi_i\geq 0, \text{ for } i=1,2,...,n \quad (3)$$

where, b is the offset plane from the origin. When compared with the number of samples the vectors are typically reduced. In distributed network, the data is mentioned in several batches. While collecting the location information, there is a drift. For example, in the vehicular network, the monitoring and surveillance are difficult because there is a dynamic in nature.

Relevance vector machine: The Relevance Vector Machine (RVM) technique has been mainly applied in pattern recognition, channel equalization and so on. In image processing applications the RVM is used for object detection. Similar to the object detection in image processing, the localization process is to be made. Hence, we modified the RVM algorithm and enhanced it functionality to make it more suitable for sensor network based applications where there exist concept drifts.

Tipping (2001) made a Relevance Vector Machine (RVM) that uses Bayesian interference and named it as the machine learning technique. Mostly, it is used to provide solutions for regression and probabilistic classification. Equation 4 shows the Gaussian process equivalent model with covariance functions. It is similar to SVM but it provides probabilistic classification:

$$k(x,x')=\sum_{j=1}^{n}\frac{1}{aj}\varphi(x,x_j')\varphi(x,x_j') \quad (4)$$

where, x, x′ are the linearly separable samples, $\varphi(x, x_j)$ is the mapping function in that x′ is one of the bias (initial) value.

Glow-worm swarm optimization: Glow-worm is the common name for various groups of insect larvae. It includes Elateridae, Lampyridae and several members of the families of Phengodidae. Krishnanand and Ghose (2009) proposed Glow-worm Swarm Optimization (GSO) as a new SI-based technique with an objective to optimize multi-modal functions. This optimization employs physical agents called Glow-worms. The Glow-worm (m), at time (t) has three main parameters. It is based on the position in the search space ($x_m(t)$), a luciferin level ($l_m(t)$) and a neighbourhood range ($r_m(t)$). They stated that these three parameters may vary with respect to the time. In Ant colony optimization, the finite regions being randomly placed in the search area, GSO has an advantage to distribute the Glow-worms randomly in the workspace. After this process, other parameters are initialized with predefined constants. The luciferin update rule is given by: $l_i(t+1) = (1-\rho)l_i(t)+\gamma J(x_i(t+1))$ where $l_i(t)$ represents the luciferin level associated with Glowworm i at time t, ρ is the luciferin decay constant ($0<\rho<1$) and γ is the luciferin enhancement constant.

Proposed optimization technique: This approach consists of relevance vector machine algorithm (Wei *et al*., 2005) to the WSN context to solve the trilateration problem. The objective is to select the innermost intersection points to calculate the position of unknown node by weighted centroid localization. After completing all the process, the Glow-worm swarm behaviour is implemented with RVM to perform geographic metrics. Finally, it is called as Relevance Vector Machine-Glow-worm Swarm behaviour Algorithm based training (RVM-GSA). Compared to that of SVM, the RVM with Bayesian formulation avoid the cross validation or set of free parameters of the SVM. However, the RVM utilized the Expectation Maximization (EM) like learning method to reduce the risk. This optimization is employed by SVM to find a global optimum. It is one of the sparse linear models to perform kernel function ϕ centred at various training phases:

$$y(x) = \sum_{i=1}^{N} w_i \phi(x-x_i) \quad (5)$$

Where:

w_i = Linear combination weights

$y(x)$ = The sparse linear model and

$\phi(x-x_i)$ = Multikernel cases

The modification of Eq. 5 results in Eq. 6, to show the multi Kernel RVM to perform distributed complex networks to find the Trilateration:

$$y(x) = \sum_{m=1}^{M}\sum_{i=1}^{N} w_{mi}\phi_m(x-x_i) \quad (6)$$

where, w_{mi} is the multi Kernel weights of RVM. In distributed network, the data propagation will be different, based on the location and its internal characteristics. It enables the automatic detection of proper kernel at each location. The main advantage of this method is that it can locate the node even if different types of nodes are in same location. Hence, the trilateration is noticed by formulating the unknown nodes as x, y and z. Next process is indentifying the location. For this process, the swarm intelligence optimization based algorithm is considered. Here, the Glow-worm based algorithm considered which is derived by Krishnanand and Ghose (2009). The algorithm reflects the behaviour of fireflies and lightning bugs. Algorithm for proposed RVM-GSA based optimization technique is given as follows:

Algorithm:
Step 1: Initialize the network size with population
Step 2: Deploy the sensor nodes randomly at different locations
Step 3: Identify the node density
Step 4: Calculate the initial node location based on RVM technique
Step 5: With respect to the node density, calculate the node weight and utilize it for finding the node with least cost
Step 6: Find the node in a particular location based on following GSO process

Represent the luciferin level of Glow-worm (i) and time (t), it is mentioned by $l_i(t)$. Find the nearest nodes (Glow-worm) that have higher intensity of luciferin. Calculate the value $l_i(t)$. For example, if i = c, then it results in $l_c(t)$. In this case, if d has the nearest location, then $l_c(t)$ moves towards $l_d(t)$. Here, c and d are Glow-worms. Updation process: It is given by:

$$l_I(t+1) = (1-p)l_i(t)+yj(x_i(t+1)) \quad (7)$$

Where:
$J(x_i(t))$ = The objective function at sensor node position or location
ρ = The delay constant, it may vary from ($0<\rho<1$)
γ = The luciferin enhancement constant
$J(x_i(t+1))$ = The value of the objective function at agent i's location at time t

Based on the node variation we need to update the process.

Find the movement phase: Select the neighbour node with the help of probabilistic mechanism. Consider a present node as 'p' and next neighbour node as 'q'. Then Probability (P) of moving p to q is calculated by:

$$P_{pq}(t) = \frac{l_q(t)-l_p(t)}{\sum_{k\in N_p(t)} l_k(t)-l_p(t)} \quad (8)$$

Where:
$l_q(t)$ = Luciferin level of neighbour node (q)
$l_p(t)$ = Luciferin level of present node (p)
$l_k(t)$ = Luciferin level of kth node
k = The size of different sensor nodes, only q uses the information of p
$N_p(t)$ = The set of Glowworm (p) neighbors at time t

The neighbourhood range updating is given by:

$$r_d^i(t+1) = \min\left\{r_s, \max\{0, r_d^p(t)+\beta(n_t-|(N_i-(t)|)\}\right\} \quad (9)$$

Where:
r_d^i = The radial range which is dynamic in nature
r_s = The sensor range
r_d^p = The radial range of node p
β = The constant parameter
n_t = The parameter for controlling the number of neighbours
$N_i(t)$ = The set of 'i' number of nodes with respect to time

Step 7: Estimate the location of node using the above steps; if the nodes are localized then estimation of unknown nodes position is succeeded. Else go back to Step 6 and proceed until it locates the position.

Normally, Glow-worms contain a luminescent substance called luciferin. The intensity of the light emitted by the Glow-worms is directly proportional to the intensity of luciferin. This process works under the scheme of radio sensing range. It means with the help of luciferin each Glow-worm may get interacted. Similarly, the movement of a sensor node (Glow-worm) is decided by the intensity of luciferin (location) possessed by its neighbours. To form a triangular mode each sensor node (Glow-worm) is attracted towards the nearest node (brighter Glow of other Glow-worms) and then it decides the point where the higher intensity of luciferin to achieve a Triangulation. This process helps to locate the nodes by separating the nodes (Glow-worms) to partition into disjoint subgroups.

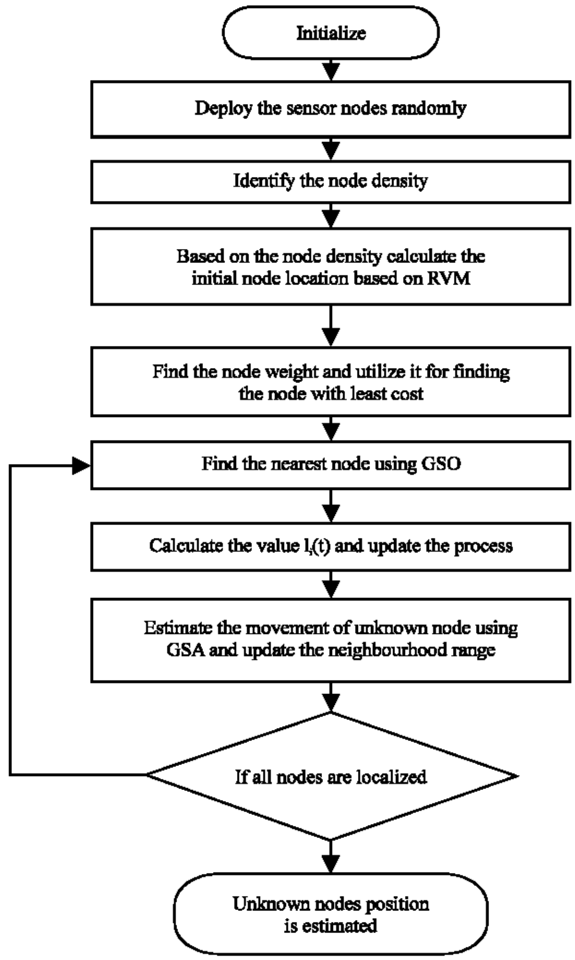

Fig. 3: Flow chart representation of RVM-GSA Model

As shown in Fig. 3, the design process starts with initialization to find the distance between anchors node and unknown nodes. Find the random location and allocate the respective distance with respect to the RVM concept and calculate the RVM parameters in each coordinate. Then, select the unknown node, for example

$n_k(k = M+1, M+2, ..., N)$. Find the distance between basic anchors and n_k. After completing the identification process, calculate the distance based on GSA process. If node is identified then estimate it and terminate, else repeat the process until it is achieved. By processing the above steps, the maximum likelihood estimation value for the unknown node is calculated.

RESULTS AND DISCUSSION

In this study, we evaluated the performance of our proposed RVM-GSO with traditional LSVM based on sensor deployment scheme with the help of MATLAB simulation. As shown in Fig. 4, black colour is the original position and red colour is predicted position of sensor nodes with different initial locations that are made randomly. The simulation model computes the location of the sensor nodes for different iteration of the deployment algorithm presented. The corresponding experimental results may follow these in X and Y position. The nodes are represented in a 100×100 m scaling position. In network communications the error rate depends upon the communication channel due to noise or any overlapping. The average error representation is made with the help of err = immse (X, Y). It provides the average error in between two same size and class domains.

From Fig. 5, we note that the average error rate increases with the radius. It means if the number of nodes gets increased, then the error rate increases. Similarly, if error decreases, the accuracy gets increased. To find the exact nature of the proposed work error rate is varied with respect to the radius of the network. As per the problem statement, the investigation is made with total population and selects the nodes which are closer to the edge. Compared to AWBCL algorithm, the proposed RVM-GSA algorithm average error rate is decreased and we got more accuracy in proposed RVM-GSA algorithm. As shown in Fig. 6, the minimum_error rates are eliminated at the closer nodes with respect to the network size. The RVM-GSA optimization based localization depends only on the Beacon nodes which is independent of other nodes. Therefore, it provides excellent separation of overlapping nodes and detects the exact location. The experimental result proves that the proposed RVM-G0SA error is reduced when compared to the AWBCL algorithm.

As shown in Fig. 7 while comparing the maximum error with radius, the AWBCL has the leading error rate which may create an unwanted distribution. Hence, it is not suitable for efficient localizing. But for proposed error rate slightly varies if the radius increases. The radius may vary to get the effective result. Finally, the computation time is represented to show the effectiveness of two methodologies. The AWBCL utilized maximum computation time when comparing with proposed RVM-GSA techniques is shown in Fig. 8.

Table 2 proves that, the computation time of the proposed RVM-GSA is reduced to 0.08466 sec when comparing with AWBCL algorithm Computation time comparison. Table 3 shows the maximum and minimum error rate for the two methods. The average localization error for proposed method has minimum of 0.0499.

The simulations result proves that the localization algorithm based on RVM-GSA has good accuracy when

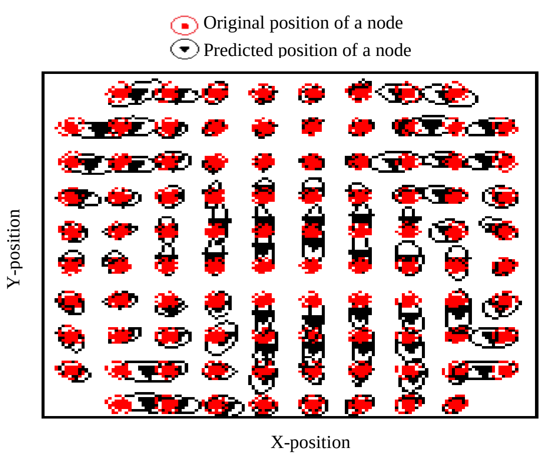

Fig. 4: Sensor node in the network area of 100×100 m

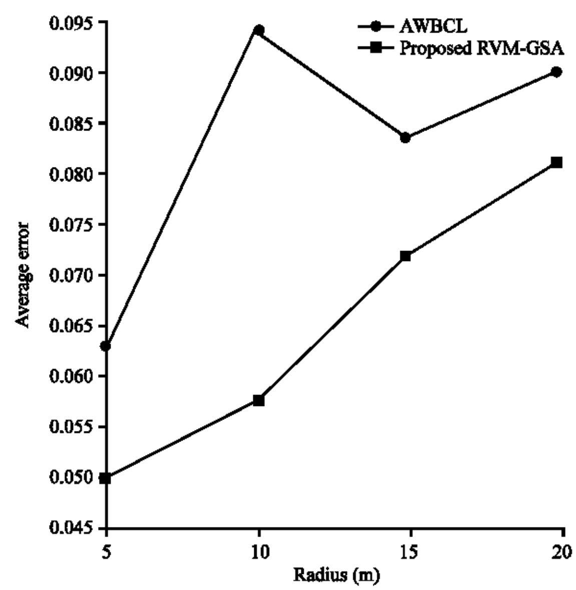

Fig. 5: Average error with respect to radius

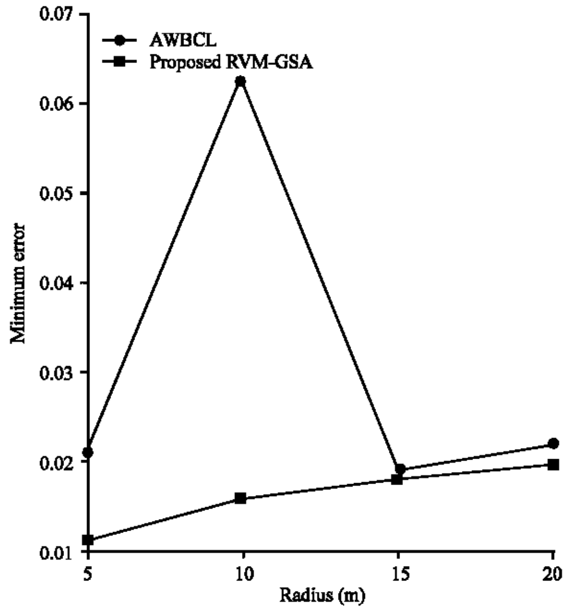

Fig. 6: Minimum error representations

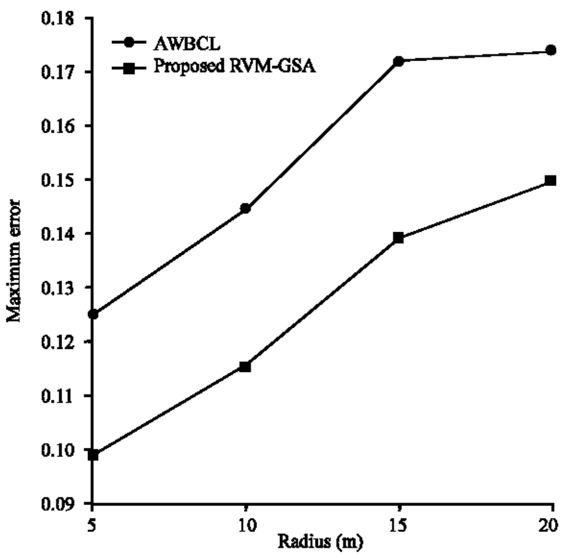

Fig. 7: Maximum error representations

comparing with the existing AWBCL algorithm. In any system, the accuracy depends on the amount of input training data. If the number of beacon nodes gets increased, the data which is available for processing is also high. Based on the complex data, this model is tested to find the accuracy. With this principle, the localization algorithm may get trained efficiently. From the experimental results, it is summarized that the proposed RVM-GSA is efficient for localization. It improves the overall accuracy and proves that it is the maximum likelihood technique to maximize the performance.

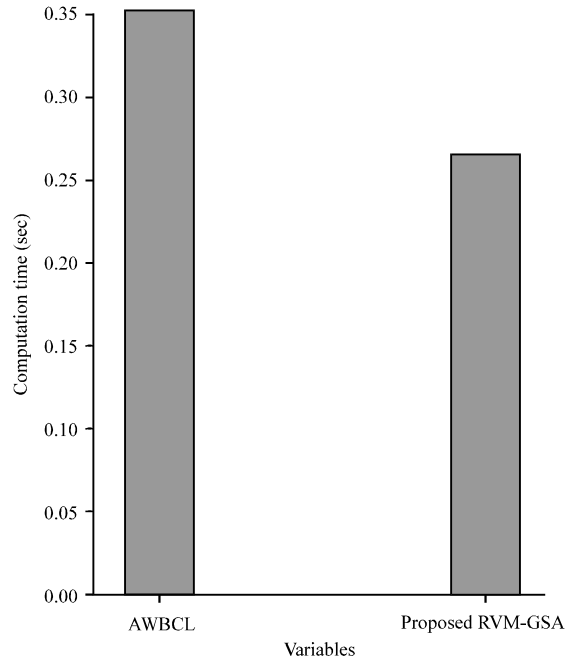

Fig. 8: Comparison of different methodologies

Table 2: Computation time

Algorithms	Computation time (sec)
AWBCL algorithm	0.34878
Proposed RVM-GSA algorithm	0.26412

Table 3: Comparison in terms of localization errors

Different algorithms/Range (m)	Max. error	Min. error	Avg. localization error
AWBCL algorithm			
5	0.1246	0.0206	0.0627
10	0.1442	0.0623	0.0936
15	0.1714	0.0189	0.0832
20	0.1732	0.0217	0.0899
Proposed RVM-GSA algorithm			
5	0.0989	0.0112	0.0499
10	0.1156	0.0159	0.0573
15	0.1391	0.0178	0.0716
20	0.1494	0.0195	0.0809

CONCLUSION

In general, localization problem is a major problem in sensor network. Though, many researchers focussed on this concept, location identification problem exists based on computation speed. Some traditional methods like SVM are used for localization but it is not efficient if the sensor network is too large. Hence, in this study, we have proposed a relevance vector machines scheme for separating the anchor nodes and finding the weight of each node. This boosted up the operating speed. After finalizing the nodes, the location is identified with the help of Glow-worm swarm optimization. This process results in maximum coverage of the sensors with limited movement after a successive random deployment. Mainly, this approach provides scalability because it does not need any centralized control. The experimental result proves that the proposed RVM-GSA error rate is reduced by 0.0128 than the AWBCL algorithm. Hence, the accuracy of the localization method also gets improved.

SUGGESTIONS

To improve the security of the proposed RVM-GSA based localization technique, it is necessary to extend this research for analyzing the unknown attacks that may affect the performance of the network. Next, it is necessary to investigate the network path under different real time training data to test and validate the localization scheme. If all the above process is made, then there is a way to use different types of mobile beacon paths under different circumstances. Final suggestions are to design the universal localization algorithm to meet the most demanding limitation of power management issues in real time issues.

REFERENCES

Abe, S., 2015. Fuzzy support vector machines for multilabel classification. Pattern Recognit., 48: 2110-2117.

Boukerche, A., H.A. Oliveira, E.F. Nakamura and A.A. Loureiro, 2007. Localization systems for wireless sensor networks. IEEE. Wirel. Commun., 14: 6-12.

Branch, J.W., C. Giannella, B. Szymanski, R. Wolff and H. Kargupta, 2013. In-network outlier detection in wireless sensor networks. Knowledge Inform. Syst., 34: 23-54.

Cortes, C. and V. Vapnik, 1995. Support-vector networks. Mach. Learn., 20: 273-297.

Das, B.B. and S.K. Ram, 2016. Localization using beacon in wireless sensor networks to detect faulty nodes and accuracy improvement through DV-Hop algorithm. Proceedings of the International Conference on Inventive Computation Technologies (ICICT) Vol. 1, August 26-27, 2016, IEEE, Coimbatore, India, ISBN:978-1-5090-1286-2, pp: 1-5.

Johann, P. and R. Hamboker, 1994. Parametric Statistical Theory. Walter de Gruyter, Berlin, Germany, ISBN:978-3-11-014030-6, Pages: 377.

Krishnanand, K.N. and D. Ghose, 2009. Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions. Swarm Intell., 3: 87-124.

Lee, J., B. Choi and E. Kim, 2013. Novel range-free localization based on multidimensional support vector regression trained in the primal space. IEEE. Trans. Neural Netw. Learn. Syst., 24: 1099-1113.

Liu, A., M. Dong, K. Ota and J. Long, 2015. PHACK: An efficient scheme for selective forwarding attack detection in WSNs. Sens., 15: 30942-30963.

Morelande, M.R., B. Moran and M. Brazil, 2008. Bayesian node localisation in wireless sensor networks. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2008), March 31-April 4, 2008, IEEE, Las Vegas, Nevada, USA., ISBN:978-1-4244-1483-3, pp: 2545-2548.

Nguyen, C., O. Georgiou and Y. Doi, 2015. Maximum likelihood based multihop localization in wireless sensor networks. Proceedings of the IEEE International Conference on Communications (ICC), June 8-12, 2015, IEEE, London, UK., ISBN:978-1-4673-6431-7, pp: 6663-6668.

Pan, J.J., S.J. Pan, J. Yin, L.M. Ni and Q. Yang, 2012. Tracking mobile users in wireless networks via semi-supervised colocalization. IEEE. Trans. Pattern Anal. Mach. Intell., 34: 587-600.

Salman, N., M. Ghogho and A.H. Kemp, 2014. Optimized low complexity sensor node positioning in wireless sensor networks. IEEE. Sensors J., 14: 39-46.

Shao, H.J., X.P. Zhang and Z. Wang, 2014. Efficient closed-form algorithms for AOA based self-localization of sensor nodes using auxiliary variables. IEEE. Trans. Signal Process., 62: 2580-2594.

Simonetto, A. and G. Leus, 2014. Distributed maximum likelihood sensor network localization. IEEE. Trans. Signal Process., 62: 1424-1437.

Tang, T., H. Liu, H. Song and B. Peng, 2016. Support Vector Machine Based Range-Free Localization Algorithm in Wireless Sensor Network. In: Machine Learning and Intelligent Communications, Xin-Lin, H. (Ed.). Springer, Berlin, Germany, ISBN:978-3-319-52729-1, pp: 150-158.

Tipping, M.E., 2001. Sparse Bayesian learning and the relevance vector machine. J. Machine Learn. Res., 1: 211-244.

Tran, D.A. and T. Nguyen, 2008. Localization in wireless sensor networks based on support vector machines. IEEE Trans. Parallel Distrib. Syst., 19: 981-994.

Wei, L., Y. Yang, R.M. Nishikawa, M.N. Wernick and A. Edwards, 2005. Relevance vector machine for automatic detection of clustered microcalcifications. IEEE. Trans. Med. Imaging, 24: 1278-1285.

Yoo, J. and H.J. Kim, 2015. Target localization in wireless sensor networks using online semi-supervised support vector regression. Sens., 15: 12539-12559.

Youssef, A.M. and M. Youssef, 2007. A taxonomy of localization schemes for wireless sensor networks. Proceedings of the International Conference on Wireless Networks (ICWN 07), June 25-28, 2007, CSREA Press, Las Vegas, Nevada, pp: 444-450.