



INTELLIGENT DEPLOYMENT OF SENSORS USING SOM IN WIRELESS SENSOR NETWORKS

Iffat Rehman Ansari

University Women's Polytechnic, Aligarh Muslim University, Aligarh 202002, U.P., India

ABSTRACT

Wireless Sensor Network (WSN) is comprised of spatially separated and dedicated sensors which monitor & record the different physical conditions of the environment and the data collected from these sensors is organized at a central location. In fact, wireless sensor networks are deployed to measure various environmental conditions such as temperature, sound, pollution levels, humidity, and wind etc. In this research paper, the probability density of events to be sensed known as event driven coverage is taken into consideration and the problem of sensor deployment particularly in an area having random distribution of events to be sensed is modeled. Firstly, an algorithm for the deployment of sensor nodes in wireless sensor networks is developed when events to be sensed are uniformly distributed throughout the target area. Secondly, the developed algorithm is modified when events to be sensed are non-uniformly distributed throughout the target area. This algorithm is based on neural network referred to as Self Organizing Map (SOM). SOM is a technique of neural network where weights associated with various neurons topologically organize themselves according to the sample data. Initially, the sensors are randomly scattered throughout the region and after running the developed algorithm, the sensors will move & distribute in the target area according to the probability of events. Thus, more information with reliability can be gathered from the region where the probability of event is higher. In this work, MATLAB is used as the programming tool to implement the algorithm.

Keywords: Wireless Sensor Network, Sensor Node, Gateway, Sensor Deployment, Target Area, SOM Neural Network, Input Layer, Competition/Output Layer, Euclidean Distance, Winning Neuron.

I. INTRODUCTION

Many recent studies have focused on different aspects of Wireless Sensor Networks (WSNs) [1]. In fact, the research on sensor networks began in 1980 and these are supposed to be the first attempts to create sensor networks [2]. Due to the advancement in micro-electro-mechanical systems (MEMS) and low power integrated circuits, there exists a number of micro sensors available with wireless capabilities. A network of these sensors called wireless sensor networks are frequently used today to perform a number of tasks such as measuring weather, seismic activity, pressure, radiation, noise, light, etc. Actually, a Wireless Sensor Network (WSN) is made up of tens to thousands of interconnected sensors that are randomly or deterministically deployed in a field of interest to monitor various environmental changes such as light, temperature, air pressure, humidity, pollution, etc. In a wireless sensor network, the issue of deployment of sensor nodes is utmost important and challenging in practice. Therefore, in this paper, simulation is performed for the deployment of sensor nodes in case of uniform distribution of events as well as non-uniform distribution of events and the simulation results for sensor deployment in an irregular area are also shown.

1.1 AN OVERVIEW OF WIRELESS SENSOR NETWORK

The architecture of a typical WSN is shown in figure (1), which consists of a number of sensor nodes deployed in a square field of interest to monitor several application-specific environmental events.

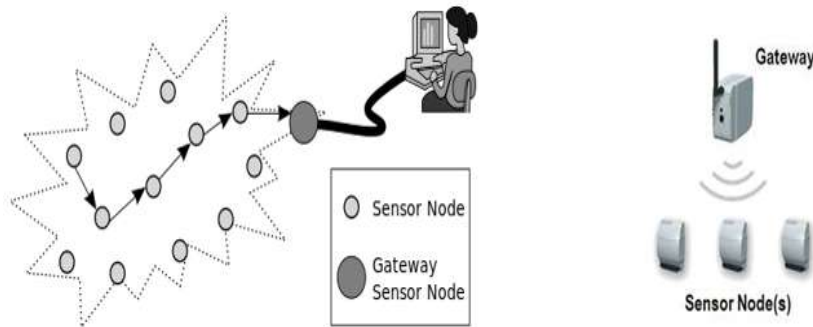


Fig. (1) Architecture of a typical Wireless Sensor Network

These sensor nodes can communicate among themselves using radio signals and they are connected to a base station (BS)/ sink node through wireless channel. A BS/ gateway acts like an interface between users and the network. The sensing data are periodically collected and aggregated at the gateway which in turn connected to a designated webserver. Thus, authorized users can remotely access and configure the WSN at anytime and anywhere [3].

One of the important unit of WSN is a sensor node and the architecture of a sensor node can be divided into four major subsystems/ units as shown in figure (2).

- Sensing unit links the wireless sensor node to the outside world
- Processing unit performs data processing and the management of node functionality
- Communication unit enables wireless communication
- Power unit provides the system supply voltage [4].

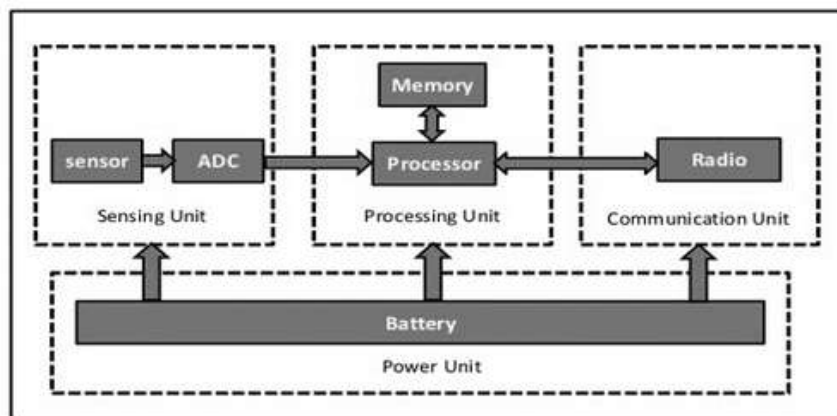


Fig. (2) Architecture of a Sensor Node

The processing unit consists of a micro-controller unit (MCU) which provides the intelligence, controls the environment to be sensed and has control over the radio component. The choice of an MCU is generally determined by the application at hand and it also affects the power dissipation of the node. An Atmel's ATmega ARM micro-controller consumes less power (16.5mW) while executing instructions, whereas Intel's Strong ARM micro-controller consumes more power (400mW) [5]. The energy source is normally a coin-like 3-4.5V



battery having 1700mAh-2700mAh capacity range [6]. In a sensor node, the environmental conditions in its surrounding are measured by the sensing transducer within certain sensing range and then, the data processor transforms the sensed data into an electric signal. After that, the processed signal is transmitted by the radio transceiver to a BS for data fusion through a direct communication path or a multi-hop communication path. All the operations including sensing, computation, and communications are powered by the embedded batteries which are usually non-rechargeable.

1.2 APPLICATIONS OF WIRELESS SENSOR NETWORKS

WSNs are an emerging technology, a new computing platform and networking structure to couple the physical world around us with digital world [7]. WSN facilitates novel applications in a wide range of disciplines [8] such as environmental monitoring, habitat monitoring, industrial and manufacturing automation, health care [9], and intrusion detection and tracking. Typical applications of WSNs include, but not limited to:

- **Environmental Observation and Forecasting Systems (EOFS):** It is a distributed WSN system designed to monitor, model, and forecast wide-area physical systems such as river systems, transportation, and agriculture for natural resource planning and disaster response [10].
- **Endangered Species Recovery:** A set of sensors are used to sense various ecological conditions such as temperature, humidity, rainfall, wind, and solar radiation near endangered plants and then the collected data can be used to investigate why a species is rare and to evaluate possible remedial actions [11].
- **Habitat Monitoring:** One of the applications of WSN is to monitor the habitat of sensitive wildlife through sampling the environmental changes in terms of temperature, humidity, barometric pressures, and midrange [12-13].
- **Intrusion Detection and Tracking:** WSN also finds its application in military for surveillance purposes such as detection, classification, and tracking of intruders/targets/objects [14] but here the main concern is that how fast the WSN can detect certain intruders/targets/objects and how reliably the sensing and detection data can be reported to the BS/ gateway.
- **Structural and Seismic Monitoring:** Another application of WSN lies in the field of civil engineering to monitor the condition of civil structures such as buildings, bridges, roads, and aircrafts for instrumentation. Due to its low cost, ease of deployment, and lack of wiring, it is supposed to be the substitute for traditional tethered monitoring systems [15-17].

II. SELF ORGANIZING MAP

Self-Organizing Maps (SOMs) or, Kohonen networks are most commonly used neural network architecture. The term “Self-Organizing Map” generally refers to Kohonen’s Self Organizing Map or, simply SOM. These maps are also referred to as “Self-organizing Feature Maps (SOFM)” [18], “Kohonen Neural Networks” [19] or, “Topological Neural Networks” [20]. Self-Organizing Maps are actually topographic maps which were first introduced by von der Malsburg in 1973. Professor Kohonen worked on auto-associative memory during the 1970s and early 1980s, and introduced SOM algorithm in its present form in 1982 [21]. SOMs also known as Kohonen feature maps are special kind of neural networks which can be used for clustering tasks. The main objective of clustering is to minimize the amount of data by categorizing or grouping similar data items

together. SOM is a highly effective and useful method for multivariate visualization as it permits the multidimensional data to be demonstrated and displayed as a two-dimensional map and this is one of its main advantage.

SOM is actually dependent on feed-forward structure with a single computational layer of neurons organized in rows and columns and each & every neuron is connected to all the source units in the input layer. The main goal of the learning algorithm for the SOM neural networks is the creation of the feature map that collects & captures the important characteristics of the n-dimensional input data and maps them on the feature space typically of 1-D or 2-D type. In practice, dimensionality of the feature space is generally limited by its visualization aspect and typically is 1, 2 or 3. In short, SOM is an unsupervised neural network algorithm which is aimed at projecting high dimensional data onto a two dimensional map. As far as this type of projection is concerned, it preserves the topology of the data. Thus, similar data items will be mapped to nearby locations on the map.

The Self-Organizing Map is based on an unsupervised and competitive learning algorithm. It is actually a sheet-like neural network having sensor nodes or neurons arranged as a regular generally two-dimensional grid [22]. An architecture of SOM neural network is shown in figure (3) which illustrates that the network consists of two layers of neurons namely an input layer and a competition layer. It uses neural networks having neurons in the output layer/competition layer competing with each other. Hence, only one neuron at a time can fire and this neuron is actually the winner neuron.

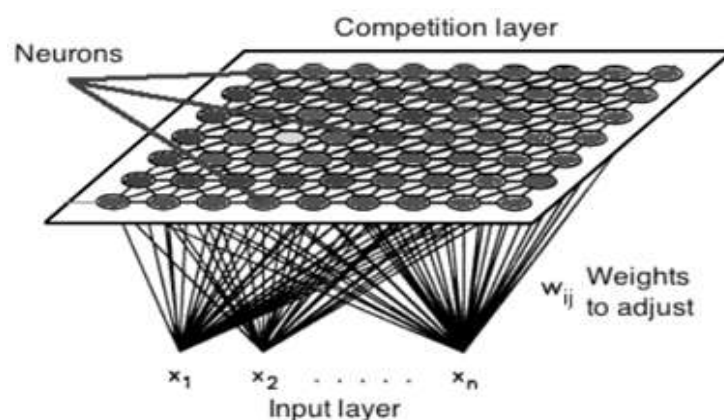


Fig. (3) Architecture of a SOM Neural Network

It can be depicted from the figure (3) that an input layer comprises of (n) nodes and an input pattern can be represented by n-dimensional vector $x_i = (x_1, \dots, x_n) \in \mathbb{R}^n$. Here, $\mathbb{R}^n$ denotes the n-dimensional space. Each neuron neu_j on the output layer is connected to all the input nodes so each neuron has (n) weights and can be represented by n-dimensional vector $w_j = (w_{1j}, \dots, w_{nj}) \in \mathbb{R}^n$. All the neurons in the output layer are usually arranged in a line (1-dimensional lattice) or in a plane (2-dimensional).

As we know that there are two neuron layers in SOFM called an input layer and a so-called competition layer. The weights of the connections from the input neurons to a single neuron in the competition layer actually denote a reference vector in the input space. It means that SOM basically represents a set of vectors in the input space that is one vector for each neuron in the competition layer. The method of finding a set of weights in such a way that for a given input the network produces the desirable output is called training and a set of pairs of

inputs along with their desired outputs is known as a training set. Generally, SOM is trained with a method of competition learning. When an input pattern is given to the network, the neuron in the competition layer whose reference vector closest to the input pattern is determined. This neuron is referred to as the winner neuron and it is supposed to be the focal point of the weight changes. In pure competition only the weights of the connections leading to the winner neuron are changed in such a way that the reference vector represented by these weights is moved closer to the input pattern. However, in SOMs not only the weights of the connections leading to the winner neuron are modified but there is also a neighbourhood function defined on the competition layer which shows the weights of other neurons should also be changed. This neighbourhood function is usually a two-dimensional grid, its vertices are the neurons and generally the grid is rectangular or hexagonal. During the learning process, the weights of all of the neurons in the competition layer which lie within a certain radius around the winner neuron with respect to this grid are also modified or adapted and the effect of this learning method is that the grid by which the neighbourhood function on the competition layer is defined, is spread out over the region of the input space which is covered by the training patterns. Because SOM learn a weight vector configuration without showing the existence of clusters at the input, then it is said to undergo a self-organized process or unsupervised learning.

2.1 TRAINING SOM

In SOM, there are two phases of operation namely the training phase and the clustering phase. During the training phase, the Euclidean distance between the current input vector and the weight set connecting the input units to a particular output unit is determined and the network selects that output node which has minimum Euclidean distance. This node is referred to as the winner node. The weights of the winner node and the weights of its neighbouring output units are updated, thus the new weight set is closer to the current input vector. This is actually the adaptation of weights and the amount of change in weight is proportional to the neighbourhood function which in turn depends on the unit's distance to the winner unit. As the SOMs require many iterations of training, so the same process is applied again & again for all input vectors until weights are stabilized. An example of a two-dimensional Gaussian neighbourhood function is shown in figure (4). As far as the choice of the neighbourhood function, the learning rate, and the termination criteria is concerned, they are all based on specific problem. Once the training phase is completed successfully then there is a clustering phase that is very simple because in this phase, only the winner unit is determined after applying the input vector.

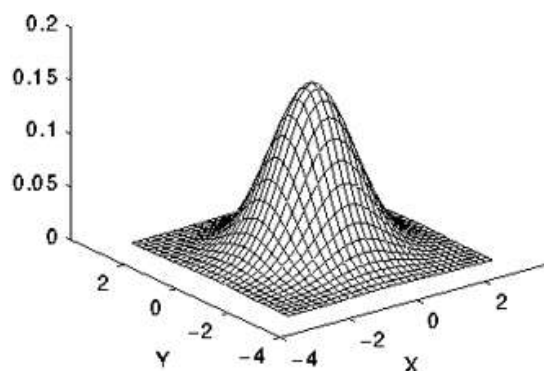


Fig. (4) Two- Dimensional Gaussian Distribution with mean (0,0) and $\sigma=1$

2.2 APPLICATIONS OF SOM

Despite the simplicity of the SOM algorithm, it can be used to perform numerous & wide variety of tasks in various important areas and its variants can be used in thousands of applications such as:

- Vector Quantization & Image Compression
- Image Segmentation
- Density Modeling
- Gene Expression Analysis
- High dimensional data visualizations
- Text Mining & Information Management
- Novelty detection
- Robotics

- Computer animation
- Clustering of genes in the medical field
- SOM based software tools in many industries
- Meteorology & Oceanography
- Mechanical & Manufacturing Engineering
- Study of multimedia & web based contents
- Data mining & Process analysis

III. DESCRIPTION OF PROBLEM & ALGORITHM DEVELOPMENT

This research work deals with the deployment of sensors and our main objective is to deploy the sensors in a target area according to the probability of occurrence of events in an efficient way. As the problem of sensor deployment has a correspondence with the SOM algorithm. Thus, SOM has been used for the deployment of sensors in a target area.

In order to perform simulation, (N) number of sensors are considered for distribution in a two dimensional target area of random shape. It is assumed that all sensor nodes are homogenous and have similar sensing capability. The sensors will be sensing events from within this area, and the events can originate anywhere in the area with a stationary and a priori known probability density distribution. Here, the disc model of sensor nodes is assumed as shown in figure (5).

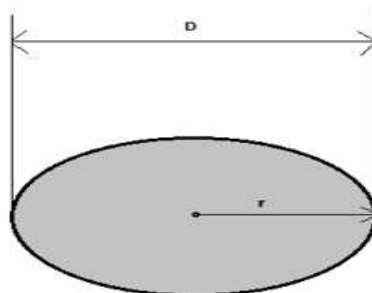


Fig. (5) Disc model of the Sensor



In this particular model, a point p in a region is covered if there exist at least one sensor within its radius (r), where r is the sensing range of the sensor. The sensor is located at the center of the disc shaped area and the shaded region denotes the sensing range of the sensor. As far as the deployment of nodes are concerned, the N sensors must be suitably and efficiently deployed to cover the target area as per expected events distribution. There is need to assign more sensors to higher probability density areas than those with areas of lower probability density. This is more desirable in the case of non-uniform distribution of sensor nodes as compared to uniform distribution of sensor nodes due to following two reasons:

- Firstly, more energy in sensing and communicating the sensed data is required in case of higher event probability since it is desirable to distribute the sensing task among multiple nodes.
- Secondly, as far as higher event probability is concerned it is actually an indication of importance of a particular region. Hence, it is desirable to deploy more sensors in areas of more activity to ensure high reliability.

In this paper, SOM is used to perform deployment of nodes in a wireless sensor network. SOM is an algorithm of neural network and the basic & fundamental steps or stages of this algorithm are as follow. Throughout these chronological steps, it is assumed that coordinates of points where events can likely to occur are known to us in priori.

1.Initialization: The random values are initially assigned to positions of sensors.

Here, $w_j = [w_x, w_y]$

where, w_x and w_y are the x and y coordinates of the positions of sensors. When sensors are thrown away in a target area from a low lying plane then they are distributed at random locations. Thus, random positions are initially assigned to the sensor nodes.

2.Sampling: A vector x_i is selected randomly from the set of training data and apply it as input. The training data sets are actually the coordinates of points where events are expected to occur.

Here, $x_j = [x_{ix}, x_{iy}]$

where, x_{ix} and x_{iy} are the x and y coordinates of the points where events are expected to occur. A very large collection of these points x_i is known as training data.

3.Matching: In this particular step, input pattern $x_i = (x_1, \dots, x_n)$ is compared with the weight vector $w_j = (w_{1j}, \dots, w_{nj})$ of each & every neuron in the output layer. The neuron whose weight vector (w_j) closest to the input vector (x_i) in terms of Euclidean distance (d_j) is known as the winner neuron and the Euclidean distance (d_j) is defined as:

$$d_j = \| x_i - w_j \| \quad (1)$$

$$\text{or, } d_j = \sqrt{\sum_{i=1}^n (x_i - w_j)^2} \quad (2)$$

where, $x_i = (x_1, \dots, x_n)$

and, $w_j = (w_{1j}, \dots, w_{nj})$

Here, (n) is the dimension of the input vector x_i and w_j is the weight vector where j varies from 1 to m . The weight vector w_j connects the input nodes (i) to the output nodes (j) or, in other words it is the position of the

sensor. The sensor which is closest to the training data is known as the winner sensor and the position of the winner sensor is determined by the following equation:

$$\text{neu}_{\text{win}} = \arg \min(d_j) \quad (3)$$

where, neu_{win} is the winning neuron or winner sensor and 'arg' denotes the 'index' of the winning neuron.

4. Updating: During training, the weights are updated according to the following equation:

$$w'_j = w_j + \eta h_{ij} \| x_i - w_j \| \quad (4)$$

where, w_j is the weight vector of the neuron neu_j and x_i is the pattern applied at the input layer. Here, η is the learning rate whose values lie in the range of $[0 \leq \eta \leq 1]$ and h_{ij} is the neighbourhood function. In SOM Toolbox, the default neighbourhood function shown in figure (6) is Gaussian Neighbourhood function which is defined as:

$$h_{ij} = \exp\left(-\frac{d_j^2}{2\sigma_t^2}\right) \quad (5)$$

where, σ_t^2 denotes the variance parameter that specifies the spread of the Gaussian function. As the training progresses, the value of this parameter decreases.

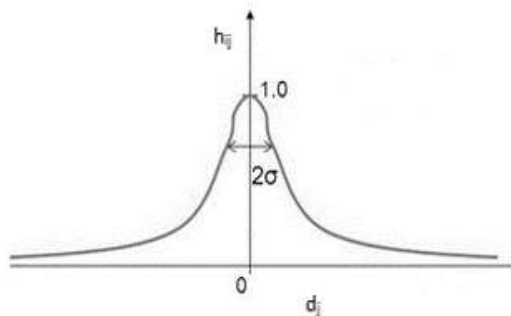


Fig. (6) Gaussian Neighbourhood Function

As far as the neighbourhood function h_{ij} is concerned, its values lie in $[0, 1]$ and it is a function of time (t). Since σ decreases with t so the neighbourhood also shrinks with time. In order to determine the distance (d_j) for this neighbourhood function, the distance in each dimension in the lattice is considered. This particular function is high (or 1) for units which are close in the output space, and low (or 0) for units far away. As the training progresses, this neighbourhood becomes smaller & smaller with the result that only the neurons very close to the winner are updated at the end of the training. When no more neuron remains in the neighbourhood, the training ends.

5. Continuation: Keep returning to step 2 until a certain stopping criterion is met or, the feature map stops changing or, the network stabilizes. A fixed number of iterations is generally the stopping criterion. In each iteration, the learning rate (η) & neighbourhood radius (r) both are decreased and thus converging to zero. This guarantees the convergence and stability of the map or network. Usually, the distance measured between the vectors is usually the Euclidean distance.

IV. RESULTS & DISCUSSION

In order to simulate the above algorithm to perform deployment of sensor nodes in a wireless sensor network, MATLAB is used as the programming tool. To carry out the simulation, a rectangular field of size 100 m x 100 m as shown in figure (7) is taken. It depicts that events are uniformly distributed throughout the target area.

When events to be sensed are uniformly distributed throughout the target area or, whole region then sensors are also uniformly distributed to provide uniform coverage for the target area as shown in figure (8).

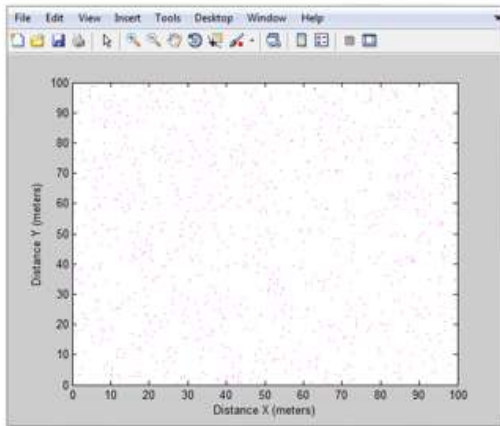


Fig. (7) Uniform distribution of Events

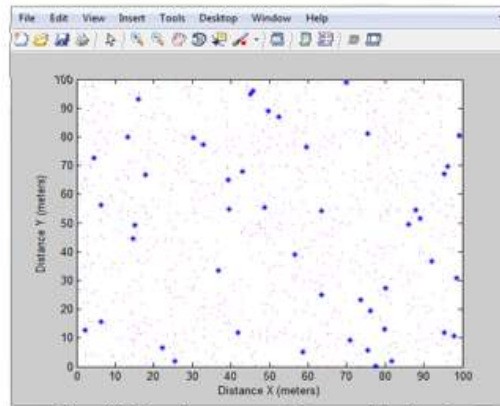


Fig. (8) Deployment of Sensor Nodes for Uniform distribution of Events

When events to be sensed are non-uniformly distributed throughout the region that is events are confined to some particular area having dimension 50 m x 50 m, then sensors can be successfully deployed using SOM algorithm and the corresponding results are shown in figure (9) and figure (10) respectively.

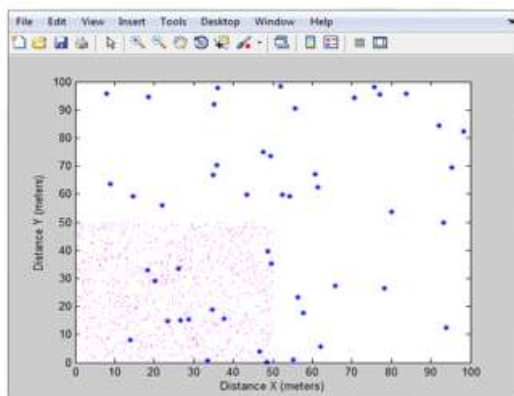


Fig. (9) Deployment of Sensor Nodes for Non-Uniform distribution of Events

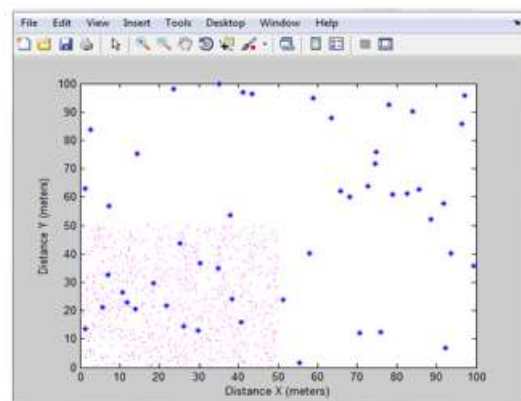


Fig. (10) Deployment of Sensor Nodes for Events concentrated at a corner

As far as the simulation results are concerned, they show that the number of sensors required for the first case when the events were uniformly distributed throughout the entire region was 8 while the number of sensors towards the corner where events are occurring has been increased to 14 or 15 for the case of non-uniform distribution of events or events are confined towards corner. Thus, the activities of the events in a confined area can be better sensed.

V. CONCLUSION

The placement of sensors at suitable points is one of the major concern in the designing of wireless sensor networks. When sensors are appropriately placed then most of the information of the target area can be well captured. In this work, sensor deployment problem in wireless sensor network is taken into account and a SOM



algorithm which is based on neural network has been developed to deploy the sensors nodes in regions where event probability is uniform throughout the region. Then this algorithm is modified for the real situation that is the distribution of sensor nodes in an irregular area where event probability is not uniform throughout the region.

It is clear from the results that SOM is successfully implemented & solves the problem of sensor deployment and it also shows an effective way of addressing coverage problem under consideration when events to be sensed are not occurring uniformly throughout the target area. It means that SOM successfully solves the problem of sensor deployment in an irregular area also and the activities relating events can be better sensed when events to be sensed are confined in a specific area. The simulation results show that sensor nodes can be successfully deployed using SOM for both the cases i.e.:

1. Deployment of sensor nodes when events to be sensed are uniformly distributed throughout the region.
2. Deployment of sensor nodes when events to be sensed are non-uniformly distributed throughout the region.

Hence it can be concluded that the method proposed here for deployment of sensors in a wireless sensor networks using SOM is an efficient and effective technique.

REFERENCES

- [1] Akyildiz, I.K.; Su, W.; Sankarasubramaniam, Y.; Cyirci, E., "Wireless sensor networks: A survey", Comput. Netw. (2002), 38, 393-422, 2002
- [2] C.Y. Chong and S. Kumar, "Sensor networks: Evolution, opportunities, and challenges", Proceedings of the IEEE Conf. Vol. 91 (8), pages 1247-1256., August 2003
- [3] Werner-Allen, G., Swieskowski, P., Welsh, M.: Motelab, "A wireless sensor network testbed", Proceedings of the 4th International Symposium on Information Processing in Sensor Networks, IEEE Press 2005
- [4] Al-Karaki, Jamal N., Kamal, Ahmed E., "Routing techniques in wireless sensor networks: A Survey", IEEE Wireless Commun., 11(6), 6-28, 2004
- [5] V. Raghunathan, C. Schurgers, S. Park, and M. Srivastava, "Energyaware wireless micro sensor networks", IEEE Signal Processing Magazine, vol. 19(2), pages 40- 50, March 2002
- [6] S. Mujumdar, "Prioritized geographical routing in sensor networks", Master's thesis, Vanderbilt University, Nashville, Tennessee, 2004
- [7] Zhao, F., "Wireless sensor networks: A new computing platform for tomorrow's internet", Proceedings of the IEEE 6th Circuits and Systems Symposium on Emerging Technologies: Frontiers of Mobile and Wireless Communication, vol. 1. pp. I-27. IEEE 2004
- [8] Sohraby, K., Minoli, D., Znati, T., "Wireless Sensor Networks: Technology, Protocols, and Applications", John Wiley and Sons Inc., New Jersey 2007
- [9] Nakamura, E.F., Loureiro, A.A.F., Frery, A.C., "Information fusion for wireless sensor networks: Methods, models, and classifications", ACM Comput. Surv. (CSUR) 39(3), 9, 2007
- [10] Xu, Ning, "A survey of sensor network applications", IEEE Commun. Mag. 40(8), 102-114, 2002



- [11] Biagioni, E., Bridges, K., “The application of remote sensor technology to assist the recovery of rare and endangered species”, Special Issue on Distributed Sensor Networks for the International Journal of High Performance Computing Applications, vol. 16(3), 2002
- [12] Mainwaring, A., Culler, D., Polastre, J., Szewczyk, R., Anderson, J., “Wireless sensor networks for habitat monitoring”, Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications, pp. 88–97. ACM 2002
- [13] Szewczyk, R., Osterweil, E., Polastre, J., Hamilton, M., Mainwaring, A., Estrin, D., “Habitat monitoring with sensor networks”, Commun. ACM 47(6), 34–40, 2004
- [14] Arora, A., Dutta, P., Bapat, S., Kulathumani, V., Zhang, H., Naik, V., Mittal, V., Cao, H., Demirbas, M., Gouda, M., et al., “A line in the sand: A wireless sensor network for target detection, classification, and tracking”, Comput. Netw. 46(5), 605–634, 2004
- [15] Krishnamachari, B., “Networking Wireless Sensors”, Cambridge University Press, Cambridge, 2005
- [16] Kim, S., Pakzad, S., Culler, D., Demmel, J., Fenves, G., Glaser, S., Turon, M., “Health monitoring of civil infrastructures using wireless sensor networks”, 6th International Symposium on Information Processing in Sensor Networks (IPSN 2007), pp. 254–263, IEEE 2007
- [17] Lynch, J.P., Loh, K.J., “A summary review of wireless sensors and sensor networks for structural health monitoring”, Shock Vib. Dig. 38(2), 91–130, 2006
- [18] Kohonen T., “Self-Organizing Maps”, 3rd ed. Information Sciences, Berlin Heidelberg, Springer 2001
- [19] Fu L., “Neural Networks in Computer Intelligence”, Singapore, McGraw Hill 1994
- [20] Niang A, et al., “Automatic neural classification of ocean color reflectance spectra at the top of the atmosphere with introduction of expert knowledge”, Remote Sens Environ. 86:257–271, 2003
- [21] Kohonen T., “Clustering, taxonomy, and topological maps of patterns”, Proceedings of the 6th International Conference on Pattern Recognition, 1982
- [22] S. Behbahani et al., “Application of SOM neural network in clustering”, J. Biomedical Science and Engineering December 2009