Self Organizing Maps based Life Enhancement Framework for Wireless Sensor Networks

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Abstract: *Wireless Sensor Networks suffer greatly from their limited battery power whose utilization is increased manifolds as a node has to transmit or receive fairly large amount of data. Several algorithms, some for scheduling battery power e.g. Dynamic Voltage Scheduling, Static Voltage Scheduling, Dynamic Power Management etc and other with emphasis on designing efficient routing protocols have been designed in past. Some algorithms, however, address this very issue at software level by writing memory and CPU friendly programs. This paper proposes Self Organizing Maps (SOM) based unsupervised Artificial Neural Network learning technique to enhance average battery life. Proposed system allows all active nodes to transmit their sensory data to the base station node (BSN) which has a 2X3 SOM running on it. Sensor nodes start sending data to the BSN; it keeps on making categories and puts relevant data in appropriate categories/ classes. SOM is trained after it has received a number of such transmissions from active nodes. Class definitions are then broadcast to all active nodes by BSN and from then onwards they transmit only the class definitions (that are fairly lesser in size) to BSN and hence significant battery power is conserved. We have showed an overall 48.5% battery power saving using the above technique*

Keywords: *Base Station Node, Self Organizing Maps, Artificial Neural Networks, Wireless Sensor Networks, Sampling, Competition, Adaptation*

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1. Introduction

Self Organizing Maps (SOM) is an unsupervised learning technique inspired by the physical arrangement of neurons within human brain. A Self Organizing Map can be one, two or three dimensional depending on the complexity of recognition or prediction task and the computational capabilities of hardware [6].

A Wireless Sensor Network (WSN) consists of very low cost and low power multifunctional sensors deployed in large number to monitor some physical activity happening within their surroundings e.g. movement of troops, measurement of temperature, humidity, vibration etc. Their implementation became possible due to recent developments in micro-electro-mechanical systems (MEMS) and state of the art communication electronics. Many real world applications are potential applications of Wireless Sensor Networks and have caught the interest of researchers from various interdisciplinary fields due to their unique characteristics e.g. an environment with large number of sensors distributed at physically scarce locations, flexibility of movement even after their deployment, self organization feature, rapid deployment and inherent intelligence [1].

SOMs have been applied to localize/ place sensor nodes in order to reduce communication overheads [5]. ART and Fuzzy ART algorithms have also been applied to sensor networks to increase battery life time and tendency for hierarchy building [9]. On the other hand, some researchers have tried techniques like Static Voltage Scheduling and Dynamic Power Management to activate electronic circuitry only when it is required [15]. The battery's life time enhancement is still an important problem. Efficient link layer protocol design for the network has also been addressed with interesting results [14]

This paper presents a novel scheme to implement a two dimensional Self Organizing Map on a sample Wireless Sensor Network to lower the volume of data packets transmitted and received within the network and hence reduction in overall battery consumption is realized. Results show that (1) Battery power saving monitored versus number of data samples transmitted for training (2) Battery power saving versus time interval between two consecutive transmissions and finally (3) an optimum operating condition was calculated by combining both of the above two dimensional plots.

Section 2 discusses the details of Wireless Sensor Networks/ IEEE 802.15.4 standard with possible routing architecture. Section 3 discusses Self Organization Maps briefly. Section 4 describes how sensory data is categorized and Section 5 describes Results and Analyses

2. Wireless Sensor Networks

Recent developments in wireless communications, integrated communication electronic design and Micro Electro Mechanical Systems have led to the development of cheap and efficient Wireless Sensor Networks. They target primarily the very low cost and ultra low power consumption applications. Data throughput of the network and reliability of a node can however be compromised to be of secondary concern [1].

Non-critical and non-real time applications in residential, business and industrial sectors have accelerated the requirement to implement inexpensive Wireless Sensor Networks and hence given rise to the concept of a model cheap wireless personal area network (LR-WPANs: Low Rate Wireless Personal Area Network) [1]. Consequently, in year 2003, the LR-WPANs standard was accepted by IEEE and was given the name IEEE 802.15.4 [11].

Suitability of Wireless Standards subsisted before the advent of IEEE 802.15.4 for applications insisting massive deployment of Wireless Transceivers was dubious due to their high cost and unnecessarily high data rate. IEEE 802.15.4 however, has revolutionized the deployment of various small sensor nodes in great numbers for monitoring various physical phenomenon, conveniently distributed at scarce locations and keeping their cost low at a compromise of low data rate and range of communication. A comparison of the 802.15.4 LR-WPANs with 802.11b WLAN and 802.15.1 Bluetooth ™ is shown in Table 1.

IEEE 802.15.4 is distinct from other wireless technologies in the sense that its goal is to achieve cheap short distance communication at low data rate and hence realization of a network of large number of very small sized nodes possible in contrast with its competitors.

The 802.15.4 LR-WPANs standard provisions two different topologies for network formation [11]:

- Star/ Hub Topology
- Peer to Peer Topology

Inspired from the conventional Ethernet Hub Architecture, Star topology only allows all active nodes to be in direct communication with Coordinator or Base station node. However, two active nodes in the field cannot be in direct communication without intervention of Base Station Node. However, Peer to Peer topology shows a different scenario, any node can communicate with any other node irrespective of intervention of base station node (BSN). Data communication in peer to peer topology is easier as compared to star topology but we have to pay the price i.e. increased network complexity.

Wireless Sensor Network/ IEEE 802.15.4 are worth using in two frequency bands (1) 868/915 MHz or (2) 2.4 GHz with the same data packet structure. However data rate can range from 20 kbps to 250 kbps as central carrier frequency increases from lowest value i.e. 868 MHz to maximum value i.e. 2.4 GHz.

Table 1. Comparison of various technologies.

	802.11b WLAN	802.15.1 Bluetooth ™	802.15.4 LR-WPANs
Range	~100m	~10-100m	10m
Data Throughput	11 Mbps	1 Mbps	<0.25 Mbps
Power Consumption	500	1000	1
Cost/ Complexity	20	10	1
Size	Larger	Smaller	Smallest

The 802.15.4 standard uses a packet structure as in figure 2. Each packet or physical layer protocol data unit contains a preamble, a start of packet delimiter, a packet length and payload field or physical layer service data unit. The payload length can vary from 2 to 127 bytes depending on size of data being exchanged. In our design, preamble carries node ID while Payload bears data from various active nodes.

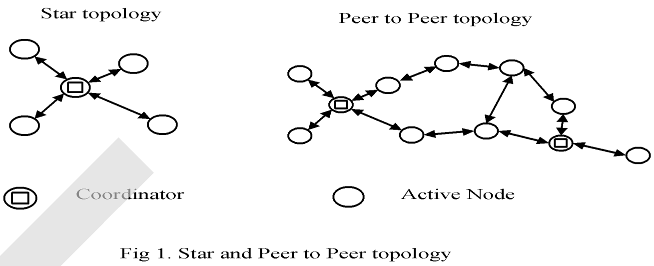

Figure 1. Star and Peer to Peer topology.

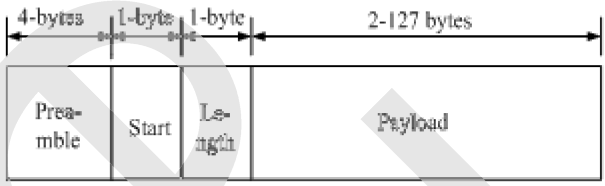

Figure 2. The IEEE802.15.4 packet structure.

3. Self Organizing Maps

An SOM [6] is a neural network that learns application information as a set of weights associated with the neurons. In comparison with other techniques (e.g. Multi-Layer Perceptron), SOMs are unique because the neurons are arranged in regular geometric structure which can be one or two dimensional. Three dimensional structures can also exist but are not very common. Neurons can be arranged either (1) Grid or (2) Hexagonal or (3) Random topology before training starts.

Topology plays a central role in learning process and on final arrangement of neurons after they have learned. Training of Self Organizing Maps in unsupervised i.e. total number of target classes is known before hand but their exact definitions are not obvious unless network is adequately trained.

Supposing input samples and the map weights to be multidimensional real valued vectors, the three phases of the training algorithm are as follows:

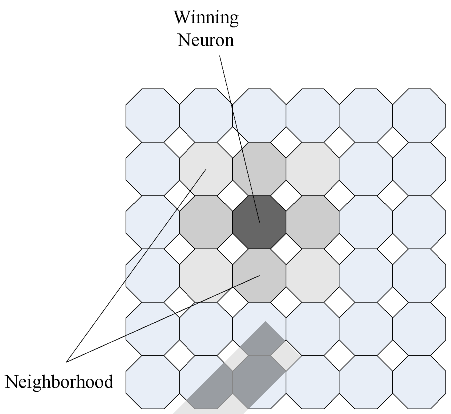

Figure 3. A 2-dimenstional Self-Organizing Map.

3.1. Sampling

An input sample taken from the training data set at a certain iteration is called *x(n)* and is applied to the network. Synaptic weight vector corresponding to a neuron j is w_j, where j ranges from 0 to t with t representing total number of neurons.

3.2. Competition

The sample $x(n)$ is compared with the map weights of each neuron through the use of a discriminating function $f = f(x,w)$. The neuron that scores the maximum value wins the competition and becomes the Winning Neuron (WN). There can be various choices for calculating distance associated with the discriminating function e.g. Euclidean, grid or box. However, if it is implemented using the Euclidean distance, the selection will be governed by the following expression:

$$WN(n) = \arg\min_j \left\| x(n) - w_j(n) \right\|$$

3.3. Synaptic Adaptation

Finally, the synaptic weights associated with Winning Neuron along with its neighbors' are adapted according to the following rule:

$$w_j(n+1) = w_j(n) + \eta(n) h(j, WN(n))[x(n) - w_j(n)]$$

Synaptic update is controlled by the global learning rate parameter η and by a neighborhood function $h = h(i, j)$ Learning rate must decrease with increasing number of iterations. Typical range of learning rate is from 0.1 to 0.01 as number of epochs increase. One possible choice for η is a decreasing exponential function given by:

$$\eta(n) = \eta_0 \exp(-n / k_1)$$

where η_0 is initial value and k_1 is a time constant.

Synaptic update also involves neighborhood function which decides how much and how far neighboring neurons should be affected in terms of their weights along with weight updating of winning neuron. The function can be Gaussian and the effect should be decreasing as Euclidean distance from the winning neuron increases.

$$h(i, j) = \exp(-\frac{d(i, j)^2}{2r(n)})$$

where d(i,j) is the distance between two neurons on the map. Weight change is significant near the winning neuron and becomes negligible on the boundary of the neighborhood range. One last parameter to be discussed is *r(n)* which is the radial distance from the winning neuron and is calculated as monotonously decreasing function:

$$r(n) = r_0 \exp(-n / k_2)$$

where r_0 is initial value and k_2 is another time constant.

r(n) is high initially, ensures early convergence of the network and becomes small as epochs increase, which causes individual neurons to become sensitive for various features contained by input data set.

4. Categorizing Sensory Data

Wireless Sensor Networks suffer greatly due to inherent loss of battery power as they process information sensed from their surroundings and then transmitting and/ or receiving this information. We have targeted this very drawback and have come up with an unsupervised learning technique i.e. Self Organizing Maps which is trained on sample two dimensional data collected from various active nodes. Once training is complete active nodes are allowed to transmit only the class titles which is less bulky as compared to full sensed data transmission. Sample input data was first plotted on a two dimensional scale to exploit any potential clusters present as shown in figure. 4.

A Self Organizing Maps based network was trained with the same training data. Output neurons were connected as a 2X3 map as shown in figure 5.

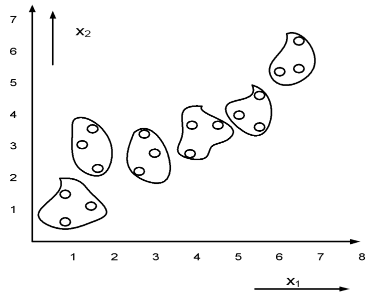

Figure 4. Sample two dimensional data.

A Self Organizing Map orders the various data samples according to their mutual similarity. The neighborhood function used was a decreasing exponential function and a variable learning rate was selected to be 0.9 initially and then decreased to 0.01as the last epoch reached.

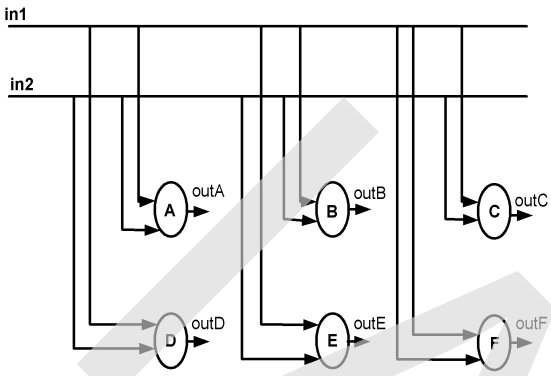

Figure 5. A 2X3 Self-Organizing Map.

The performance of the above 2X3 Self Organizing Map was compared with a feed forward backpropagation network with one hidden layer and six output neurons as shown in figure 6.

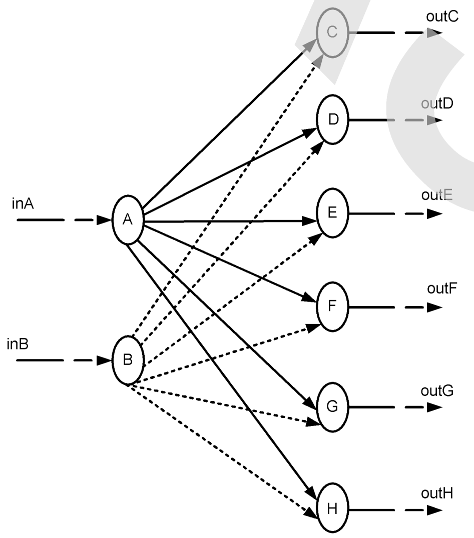

Figure 6. Feedforward network with 6 output neurons.

The SOM was found advantageous in terms of its very early convergence. Performance of Self Organizing Maps algorithm was verified for some of the input samples whose calculation is given in the next section.

5. Result and Analyses

Implementation of a 2x3 Self Organizing Map neural network learning on one wireless sensor network active node can result in a significant power saving which will be obvious as we move further in this section.

Power dissipation of a typical WSN node for various operations is given in table 2.

Table 2. Power Consumption of various operations.

Operation	**Power Consumption**
Central Processing Unit (CPU)	3 mW
Transmitter	35 mW
Receiver	38 mW
Sleep	5 µW

There are two major factors affecting overall power savings achieved by the scheme.

- Total number of training data samples
- Interval between two consecutive transmissions (after the network is trained)

In each case the power saving was the calculated difference between "power consumed if there is no training" and "power consumed by training/ trained network".

Table 3. Power Saving Chart.

Interval b/w consecutive transm-issions (hours)	**Power Saving** (mW)					
	Training Data Samples					
	18	**19**	**20**	**21**	**22**	**23**
2	23	23	22.5	22.5	22	21.5
4	37	36	35	34.5	33.5	32.5
6	44.5	43	41.5	40.5	39	37.5
8	48.5	46.5	44.5	42.5	40.5	39
10	49.5	47	44	42	39.5	37.5
12	48.5	45.5	42.5	39.5	37	34.5
14	44.5	41	38.5	34	30.5	27.5
16	38.5	34	30	26	22.5	19
18	34.5	30.5	25.5	21	17	14.5
20	30	25.5	21	16.5	12.5	9
22	25.5	20	16.5	11.5	8	4.5
24	21	15.5	11	6.5	2	2

If the total number of training data samples is kept low, the network will not be able to converge. However, power consumption will be small. On the other hand, as the number of training samples is increased, the network will be converged adequately but at a cost of increased power consumption.

The time interval between two consecutive transmissions was kept constant and power saving was calculated for varying values of training data samples which, in each case, were varied from 18 to 23. This is done by reading data of Table 3 one row at a time.

Six different plots were obtained by changing time interval between two consecutive transmissions from 4 to 24 hours as shown in figure 7.

5.1. Power Saving vs Interval between Transmissions

After the network is trained, if transmissions are made frequent, the battery will exhaust drastically but with the benefit of continuous monitoring. On the other hand, if interval between two consecutive transmissions is larger, the life time of voltage source will increase (with some conditions discusses later in this section) but at a cost of weak monitoring.

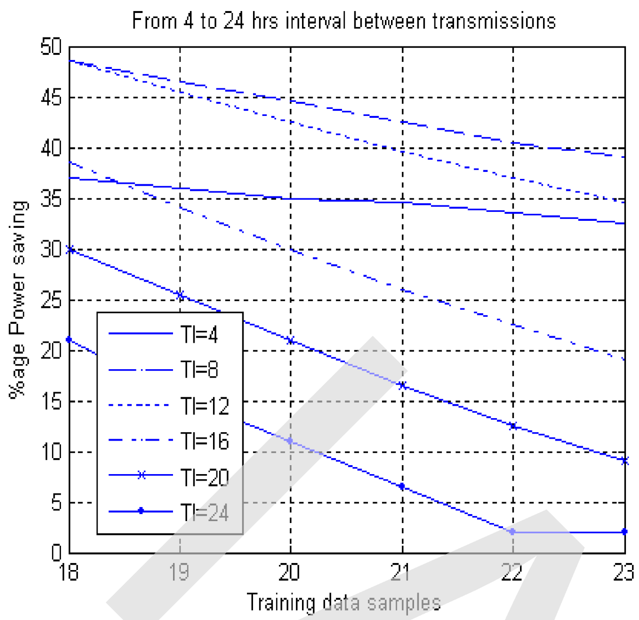

Figure 7. Power Saving versus Training Data Samples.

Training Data Samples were kept constant and power saving was plotted versus interval between two transmissions which in each case, was varied from 2 to 24 hours. This is done by reading data of Table 3 one column at a time.

Six different plots were created by varying training data samples from 18 to 23 which are shown in figure 8. Figure 8 reveals that the power saving increases initially with increasing time interval between transmissions but as time interval crosses a certain value, it starts decreasing. It is due to the fact that if data transmissions are not frequent then the power consumed to train the network initially, becomes an overhead.

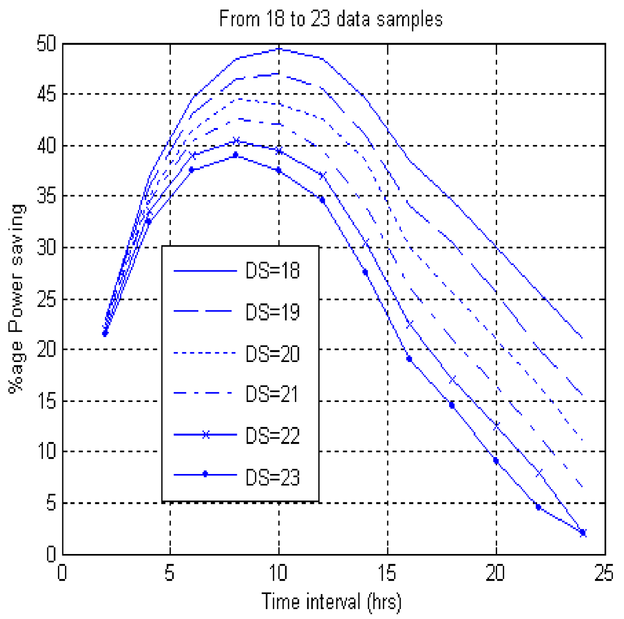

Figure 8. Power Saving versus Time Interval between transmissions.

5.2. Power Saving vs Time Interval and Training Data Samples

The effect of “Time interval between transmissions” and the “Number of training data samples” on “Power Saving” is shown in figure 9.

From this plot we can infer the optimum values of training data samples and time interval between consecutive transmissions required to maximize overall power saving. Optimum parameters derived from figure 9 are given in table 4.

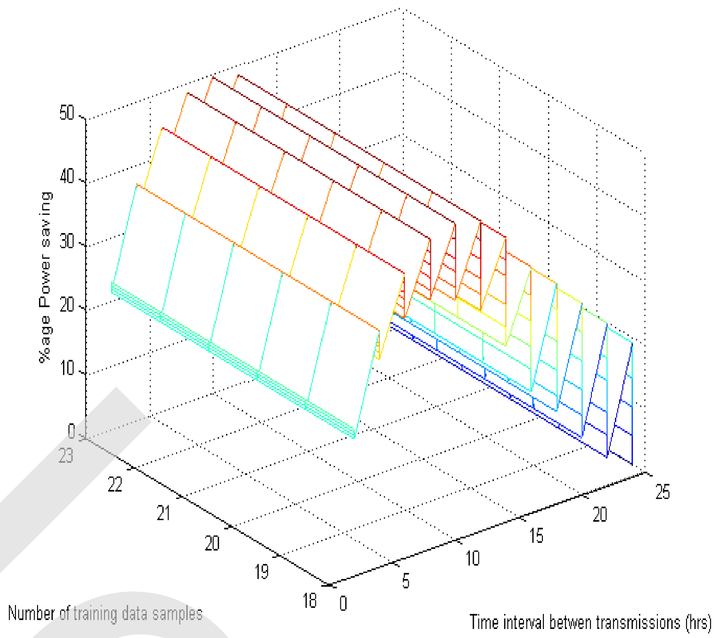

Figure 9. Power Saving versus Time Interval and Training Data Samples

Table 4. Optimal parameters.

Optimum number of training data samples	18
Optimum Time interval between two consecutive transmissions	9.5 hrs
Maximum Normalized Power Saving achieved	48.5%

6. Conclusion

Wireless Sensor Networks suffer greatly due to inherent loss of battery power as they process information sensed from their surroundings and then transmitting and/ or receiving this information. We have targeted this very drawback and have come up with an unsupervised learning technique i.e. Self Organizing Maps which is trained on sample two dimensional data collected from various active nodes. Once training is complete active nodes are allowed to transmit only the class titles which is less bulky as compared to full sensed data transmission. We have shown that applying this technique to two dimensional sensed data has resulted in enormous battery power saving which is around 48.5%.

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