

Effect of Localization Accuracy on Battery Consumption of Nodes in Wireless Sensor Networks

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Abstract— Wireless Sensor Networks (WSNs) are often employed to work in unattended, unreachable and may be hostile environments where replacing node battery may be an impossible task. The process of knowing the origin of monitored event is called localization. Also sensor node/network lifetime depends strongly on battery lifetime. Due to the fact that replacing batteries manually in the field is impossible, several researches are on to find techniques to prolong the battery lifetime. This work attempts to study the effect of localization accuracy on battery lifetime and hence the network lifetime.

Index Terms— Localization, neural network, wireless sensor network.term

I. INTRODUCTION

Day-to-day advances in wireless communication and MEMS (Micro Electro Mechanical Systems) technology have enabled the production of tiny sensor nodes that integrate small size sensor, processor, memory and power supply in it [1]. Group of such sensor nodes connected wirelessly in a network are referred to as wireless sensor network (WSNs). These small, multifunctional, cheap, powerful and smart sensors have increased the applications of WSNs even in areas where human life is unsafe like monitoring volcanic eruptions, radioactive areas, disaster rescue operation and military applications like battlefield surveillances etc. Apart from these other areas of applications are habitat monitoring, scientific research, etc., [2]. In most of these applications, it is very important to know from where the sensing data has arrived i.e. the location estimate of sensor nodes is also required that helps the scientists or researchers to further processing. Nodes in WSN are battery constrained. Also sensor node/network lifetime depends strongly on battery lifetime. Due to the fact that replacing batteries manually in the field is impossible, various techniques can be employed to prolong network lifetime. This work attempts to evaluate the effect of Localization accuracy on battery lifetime.

The determination of node location or geographical location of sensor node is localization which has become an

authoritative topic for researchers. It is considered a cardinal service that is similar to various important operations like cluster creation, routing, communication, coverage of network, etc [3], without involvement of human beings. Localization can be attained from sensor node itself. In such schemes there are two types of sensor nodes: landmark nodes that are aware of their position unknown sensor nodes estimate their position using these landmark nodes. An aboveboard approach for localization is using of GPS, but not viable as this increases the cost, size, etc of the sensor node. Localization techniques are broadly classified into two methods: *range based* and *range free*. In *range based* techniques node to node distance/angle is estimated using several methods such as ToA, TDoA, RSSI and AoA [4-6] with requirement of some hardware, but they have less location error compared to *range free* techniques. *Range free* technique only requires the radio connectivity between sensor nodes to estimate their locations. Figure 1 show the various steps involved in localization of the nodes [7].

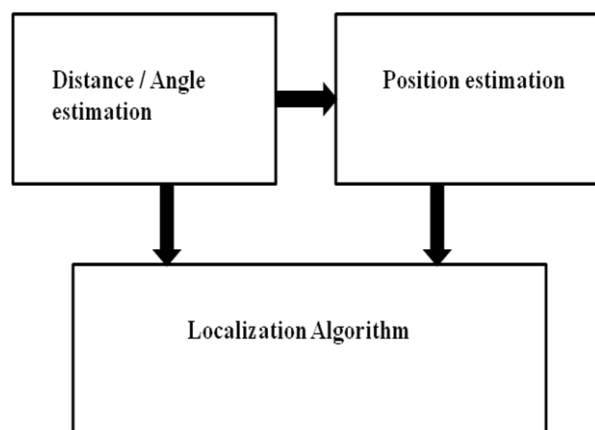


Figure 1. Steps in localization of nodes

Further sections in this research work are as follows: Related work on Multidimensional scaling and neural network is described in section II with a detailed description of classical multidimensional scaling (CMDS) in next

section III. Section IV includes Neural Network description followed by simulation scenario and implementation using QualNet version 5.2 followed by parameters in section V. Section VI contains conclusion and future work.

II. RELATED WORK

Yi Shang *et al.* in [8] present an algorithm that uses connectivity information—who is within communications range of whom—to derive the locations of the nodes in the network. Results show that algorithm is more robust to measurement error, especially when nodes are positioned relatively uniformly throughout the plane. Yi Shang *et al.* in [9], demonstrate new MDS-MAP(P) method which gives good performance of original MDS on relatively uniform layout and also perform much better than the original on a irregularly-shaped network. Georgios Latsoudas *et al.* in [10] proposed a two-stage MDS algorithm utilize an algebraic initialization procedure followed by gradient descent. The algebraic initialization step is based on the Fastmap algorithm. Fastmap is a linear-complexity mapping tool, which is, however, sensitive to measurement errors. Ali Shareef *et al.* in [11], indicate that neural networks are a viable option for solving localization problems. they qualitatively compare the performance of three different families of neural networks: Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and Recurrent Neural Networks (RNN), then compared the performances of their network with two of the Kalman Filter which are traditionally used for localization. Their result shows that the RBF neural network has the best accuracy in localizing, however it also has the worst computational and memory resource requirements. The MLP neural network, on the other hand, has the best computational and memory resource requirements. The works so far have not considered the effect of Localization accuracy on battery lifetime of a node. This work attempts to evaluate the effect of Localization accuracy on battery lifetime.

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III. CLASSICAL MDS

Classical MDS (Classical Multidimensional Scaling) techniques solve for reverse problem of estimating position of nodes using given distances between each pair of them using the connectivity information between nodes in the communication range, and also localize sensor nodes without using landmarks or GPS.

A. Algorithm used for localization

Consider two objects (sensor nodes) p, q with dissimilarity measure (distance between objects) d_{pq} . Euclidean distance between two objects.

$X_p = (x_{p1}, x_{p2}, \dots, x_{pm})$ and

$X_q = (x_{q1}, x_{q2}, \dots, x_{qm})$ i.e.

$$d_{pq} = \sqrt{\sum_{k=1}^m x_{pk} - x_{qk}} \quad (1)$$

equation (1) yields a pair wise distance matrix D (where $d_{pp} = d_{qq} = 0$) Classical MDS algorithm localize the sensor node using squared and double centered version of matrix D , denoted by S given in equation (2).

$$S = \frac{1}{2} J R J \quad (2)$$

where $R = D \cdot D$ (matrix of element wise squared distance) and J is the centered operator given in equation (3).

$$J = I - \frac{ee^T}{N} \quad (3)$$

where e is an $N \times 1$ vector of 1's, N is a number of objects and I is an identity matrix.

Eigen value decomposition of matrix S is computed as

$$S = UV^T \quad (4)$$

thus node coordinate is an eigen vector and eigen value scaled by square root of matrix S [10, 12].

IV. NEURAL NETWORK

Artificial neural network (ANN) is a mathematical model derived from biological neural network. Now a days this technology is new as compared to other signal processing technology. In this, artificial neurons are interrelated with each other according to network architecture. As they change their architecture during learning phase, they are also known as adaptive filter. Using weight function along with an input vector, and also with a learning phase they produce output as per requirement.

V. SIMULATION SCENARIO

Here we have used Qualnet 5.2 version simulator over Windows platform for this research work. Qualnet is a discrete event simulator. The terrain size selected is $1m \times 1m$ with 50 nodes connected wirelessly along with 10 constant bit rate applications (CBR) with simulation time

of 501 seconds. Fig 2 & 3 shows scenario without NN and with NN using Fisheye routing protocol.

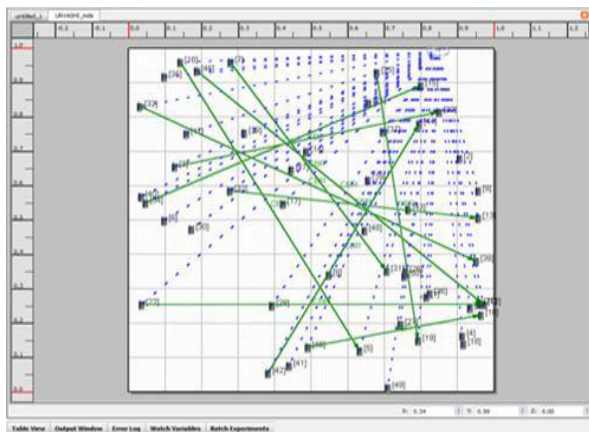


Figure. 2 Scenario without NN using Fisheye routing protocol

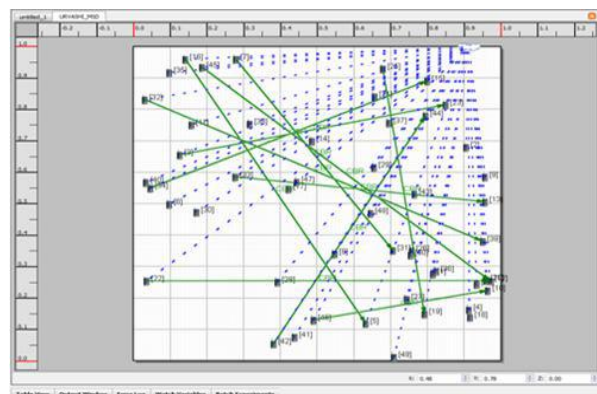


Figure.3 Scenario with NN using Fisheye routing protocol

The result of CMDS implementation was fed to NN in MATLAB to obtain the mapping of the nodes. CMDS results give an estimate of nodes. This estimate is fed to NN to obtain better estimate of nodes. The result obtained on CMDS with & without NN implementation was tested for various parameters such as (a) total packet received (b) energy consumed in idle mode (c) energy consumed in transmit mode. The simulation results obtained over MATLAB indicate higher localization accuracy after NN implementation. These results are tested over QualNet to verify the effectiveness of higher localization accuracy on battery lifetime of node.

The results of following parameters obtained after using Qualnet are as follows: Figure 4 shows total packet received. It indicates that total packet received using CMDS without NN are less as compared to with NN implementation. Total packet received without NN are 5968 and with NN are 5973.

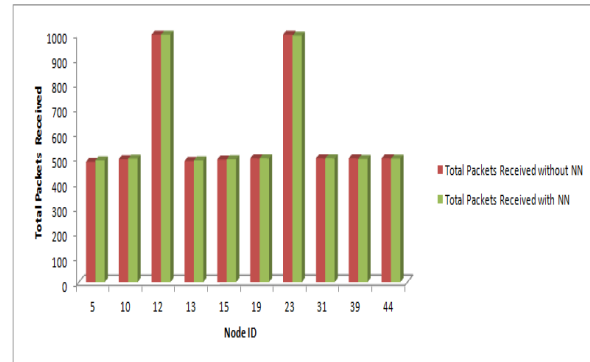


Figure. 4 The total number of packets received.

Figure 5 shows energy consumed in idle mode without as well as with NN implementation. In this energy consumed with neural network implementation is very less as compared to without NN. This means that during idle mode, battery consumption is lower with higher localization accuracy.

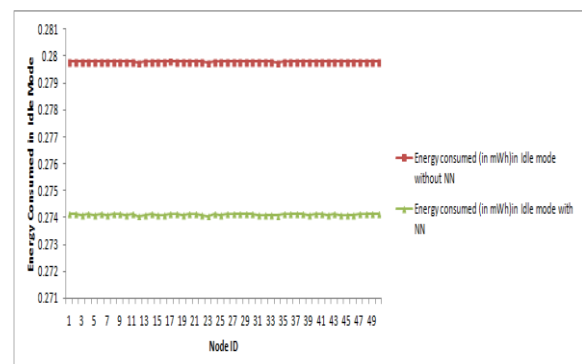


Figure. 5 Energy consumption in idle mode.

Figure 6 shows energy consumed in transmit mode which is almost same for both condition.

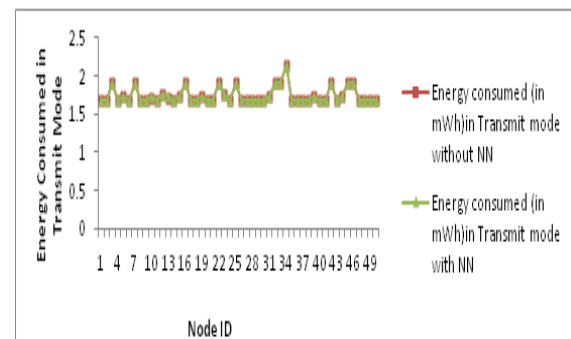


Figure. 6 Energy consumption in transmit mode.

VI. CONCLUSION

Energy consumed in a node is during transmit, receive and idle mode apart from energy consumed during retransmission in case of collisions. The implementation results show that energy consumed during idle time with higher localization accuracy is quite low. It is quite evident that battery power consumption shall reduce with better

localization accuracy. In this work NN has been used to obtain better that will increase the burden on already constrained nodes. Hence alternative localization techniques have to be developed without burdening the nodes to obtain high localization accuracy.

REFERENCES

- [1] Mehak Khurana, Ashish Payal, "AnImprovement of Centroid Algorithm Based on Distance in Wireless Sensor Network", *International Journal of Smart Sensors and Ad Hoc Networks (IJSSAN)* Volume.1, Issue.1, 2011, pp.28-32.
- [2] Yingpei Zeng. Jiannong Cao. Jue Hong. Shigeng Zhang. Li Xie , "Secure localization and location verification in wireless sensor networks: a survey", *J Supercomput* DOI10.1007/s11227-010-0501-4, Springer Science+ Business Media, LLC 2010.
- [3] S. Swapna Kumar, Dr. M. Nanda Kumar, Dr. V.S Sheeba, "Obstacle base Range-free Localization -Error estimation for wireless sensor networks", *International journal of Computer Science Issue (IJCSI)*, Issue, Volume.8, Issue 5, No.2, September 2011, pp.31-39.
- [4] Rongbiao Zhang. Lili Zhang. Youbing Feng, "Very Low Energy Consumption Wireless Sensor Localization for Danger Environments with Single Mobile Anchor node", *Wireless Pers Commun* (2008) 47:497–521 DOI 10.1007/s11277-008-9496-z, Springer Science+ Business Media.
- [5] Amitangshu Pal, "Localization algorithm in WSN: current Approaches and future challenges", *Network Protocols and Algorithm ISSN* 1943-3581 Volume.2, No.1, pp.47- 73, 2010.
- [6] Attoungble Kouakou Jean Marc, Okada Kazunori, "LRD : A Distributed and Accurate Localization Technique for Wireless Sensors Networks", *TENCON* 2010- 2010 IEEE Region 10 Conference. pp. 234-239.
- [7] Azzedine Boukerche, Horacio A.B.F, Oliveira, Eduardo F. Nakamura, Antonio A.F. Loureiro, "Localization Systems For Wireless Sensor Networks", *Wireless Sensor Networking, IEEE Wireless Communications*, December 2007, pp. 1-12
- [8] Yi Shang, Wheeler Ruml, Ying Zhang, Markus P. J. Fromherz, "Localization from Mere Connectivity", *Proceeding MobilHoc '03 Proceedings of the 4th ACM international symposium on Mobile ad hoc networking & computing*, pp.201-212, ACM New York, NY, USA© 2003.
- [9] Yi Shang, Wheeler Ruml, "Improved MDS-Based Localization", *INFOCOM* 2004. Twenty-third Annualjoint Conference of the IEEE Computer and Coounications, Date of conference 7-11 march 2004, *Deptt. of Comput. Sci., Missouri- Columbia Univ., Columbia, MO, USA* Volume 4, pp. 2640-2651.
- [10] Georgios Latsoudas, Nicholas D.Sidiropoulos, "A Fast and Effective Multidimensional Scaling Approach for Node Localization in Wireless Sensor Networks", *IEEE transaction on Signal Processing*, Volume.55, No.10, October 2007, pp.5121-5127.
- [11] A Shareef, Y. Zhu and M. Musavi, "Localization using neural networks in wireless sensor networks", *Proceedings of ACM first International Conference on Mobile Wireless Middleware, Operating Systems, and Applications (Mobileware)*, Innsbruck, Austria, February 2008.
- [12] Rashmi Agrawal, Brajesh Patel, "Localization in wireless sensor network using MDS", *International Journal ofSmart Sensors and Ad Hoc Networks (IJSSAN)* ISSN No. 2248-9738 Volume.1, Issue-3, 2012, pp. 26-31.



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