

Energy efficient Multi-Target Tracking in Wireless Sensor Networks with accuracy

G.Suresh Kumar,
Associate Professor,
Sethu Institute of Technology,
Kariapatti,
Tamilnadu,
India.

V.Rajamani,
Professor,
Indra Ganesan College of Engineering,
Tiruchirapalli,
Tamilnadu,
India.

ABSTRACT

Wireless Sensor Networks (WSN) depend on the algorithms and protocols for Communication and Computation. In this paper, the target tracking application in WSNs consist of active sensors. Sensor senses the environment actively by emitting energy and measuring the reflected energy. In the algorithm, a presentation of novel collaborative sensing scheme is used to sense the multiple targets and high maneuvering targets in an energy efficient method. Joint sensing can increase the sensing region of an individual emitting sensor and generate multiple sensor measurements simultaneously. In order to conserve energy, the sensors may be put into sleep mode. Adaptive Scheduling is used to estimate the target velocity using sensor measurements, to predict the target movement. Joint Sensing is used to track the targets accurately as compared to the individual sensing. Multiple and high maneuvering targets are identified with energy efficiency.

Key Words

quality of information; target tracking; joint sensing; sensor scheduling; Adaptive Scheduling

1. INTRODUCTION

Typically, a Wireless Sensor Network (WSN) is application-driven and mission-critical. Therefore, the Information Quality (IQ) or Quality Of Information (QoI) such as the accuracy of target tracking or event detection is critical for the end users, service providers and the system designers. To provide accurate IQ in WSNs is challenged due to the resource-constrained, dynamic and distributed nature of the network and the lack of a holistic design approach. This takes as different types of resources and their inter-dependencies. Recently, IQ is receiving increasing interests for various WSN applications. For example [4] explains about dynamic Bayesian network, sensor selection approaches for human activity detection are proposed to optimize IQ represented by the entropy of the detection probability. In [3], the relationship between the sensor sampling rate and the QoI metric of timeliness and confidence is derived. In [5], the entropy of sensory data is used to quantify the IQ.

Based on the exponential correlation model for the sensory data, an asynchronous sampling strategy is proposed to improve the IQ through shifting the sampling moments of sensors. Target tracking in WSNs has been studied extensively. Due to the limited sensing capability and limited resources for communications and computation, collaborative resource management is required to trade-off between the tracking accuracy, i.e., the IQ of the target

tracking application and the resource usages, e.g., through selection of single tasking sensor or multiple tasking sensors. A distributed market-based congestion scheme in [2] is used for competition of allocated time slot in a node among multiple target tracks with different QoI and priorities. Ultrasonic WSN test-beds for target tracking are also developed using centralized architecture and distributed sensor competition to show the IQ of different sensor scheduling schemes.

In general, sensors used in WSNs are classified into active and passive ones. Passive sensing mechanism is used in acoustic, seismic or thermal sensors, where the sensor measures the energy already in the environment. A sensor adopting the active sensing mechanism, like the ultrasonic sensor, senses the environment actively by emitting energy and measuring the reflected energy. To the best of knowledge in the existing literature, the tasking sensor works independently on other sensors for individual measurement. Based on active ultrasonic sensors, it will introduce a joint sensing mechanism by using single sensor to emit the energy and multiple sensors to measure the reflected energy signals from the target to present a novel collaborative sensing scheme using joint sensing and adaptive sensor scheduling to select the emitting sensor for the next time step. In according to the predicted target detection, probability of the emitting sensor cost? Sensor selection based on the expected information gain is introduced for a decentralized sensing system. An entropy-based greedy heuristic approach is proposed to sequentially select tasking sensors to reduce the localization uncertainty.

2. LITERATURE SURVEY

2.1 Vaidehi.V, S.Vasuhi, K. Sri Ganesh, C. Theanammai, Naresh Babu N T, N Uthiravel, P.Balamuralidhar and Grish Chandra "Person Tracking Using Kalman Filter in WirelessSensor Network" on ICoAC 2010 pp 60-65[15]

Wireless Sensor Network (WSN) is an emerging technology for person detection and tracking. This paper proposes a scheme for detecting and tracking a person using WSN. In an organization where employees possess unique Radio Frequency Identification (RFID) tags, a WSN node detects the presence of a person using a PIR sensor and the identity of the person is obtained from the RFID tag. The accuracy of tracking a person in a WSN is limited due to the sensor's detection capabilities. Also, the sensor packets may be lost in the wireless medium. Moreover, the location information in the sensor is not accurate indoors. This paper proposes a multi-sensor and Kalman Filter (KF) based tracking scheme in a WSN oblivious to localization errors, errors due to

missing events caused by failure of nodes etc. The accuracy of the proposed tracking has been validated for different scenarios. This paper proposes a Kalman filter-based person tracking scheme in WSN which is a module in the person detection and tracking project. The movement of the person is detected by the PIR sensor and the position of the person is obtained using RFID reader. Kalman filter predicts the next position of the person. The proposed scheme has been validated using simulation studies. Research is in progress to integrate the RFID, PIR sensor data with an imaging sensor to detect and identify an intruder.

2.2 Dan Liu, Nihong Wang and Yi An “Dynamic Cluster Based Object Tracking Algorithm in WSN” 2010 Second WRI Global Congress on Intelligent Systems pp 397-399[16]

The authors proposed dynamic cluster based algorithm. The algorithm wake up or sleep at the sensing nodes though predicting the moving track of the target, which reduces the number of tracking nodes to minimize network energy consumption. Selecting the optimal nodes to conduct the tracking task along the predicted moving track though the energy consumption of communication function, which guaranteed load balancing and extend the network lifetime. Extending the network’s lifetime and showing the improvement in tracking accuracy are important goals. The proposed object tracking algorithm based on Dynamic Cluster Tracking Algorithm (DCTA) in paper rationally uses the organization of network to ensure tracking accuracy and reduce network Consumption. DCTA focus on the establishment of dynamic cluster and prediction based on object moving state, select node which could take better quality tracking by means of optimal selection function and save energy effectively. Experiments show that DCTA algorithm can extend network lifetime and guarantees the tracking accuracy.

Supreet Kaur Sarna and Mukesh Zaveri “EATT: Energy Aware Target Tracking for Wireless Sensor Networks Using TinyOS” on 978-1-4244-5540-9/10 IEEE 2010 pp 187-19[20]

Wireless Sensor Networks consist of various sensor nodes which operate in a memory, energy and bandwidth constrained environment. Target tracking is an important application in Wireless Sensor Networks and the authors proposed an Energy Aware Target Tracking (EATT) algorithm. Energy efficiency is obtained due to the novel concept of tracking being performed in a collaborative manner by different cluster heads instead of using a base station. This helps to minimize the energy required for communication. Taking into consideration the unique energy constraints of motes the authors reduced the computational complexity of the tracking algorithm by using simple optimization technique. The authors discussed about tracking approach and then focus on the advantages of program optimization in wireless sensor networks. The work presented demonstrates the viability of achieving real time energy efficient target tracking by using simple optimization technique for a tracking algorithm implemented in TinyOS. The simulation results show that the proposed technique reduces the energy consumption by at least 20% and memory requirement by at least 6% as compared to the conventional techniques used in Wireless Sensor Network.

2.4 Yousef E. M. Hamouda and Chris Phillips “Metadata-Based Adaptive Sampling for Energy-Efficient Collaborative Target Tracking in Wireless Sensor

Networks (WSNs) are being employed have driven the desire for energy-efficient reliable target tracking. In this paper, a biologically inspired, adaptive energy-efficient multisensor scheme is proposed for collaborative target tracking in WSNs. Behavioral data gleaned whilst tracking the target is recorded as metadata to maintain the tracking accuracy. The group of tasking sensors that track the target is selected proactively according to the information associated with the predicted target location probability distribution. One of the selected tasking sensors is elected as a main node for management operations to improve the energy efficiency. Simulation results show the developed adaptive multisensor scheme can achieve a significant reduction in energy consumption and seamless tracking compared with uniform sampling interval schemes.

Future work is now focusing on considering the node resources in the selection and election algorithms. Adaptive group size management will be considered to maintain a fixed tracking accuracy. A recovery protocol will also be implemented in case of poor predicted target state PDF.

2.5 Yan-Xiao Li, Le-Bin Lu and Dong-Yang Liu “Research on Battlefield Target tracking in Wireless Sensor Networks” on 978-1-4244-6977-2/10/ 2010 IEEE[13]

Due to the uncertainties in target motion and limited sensing regions of sensors, collaborative target tracking in Wireless Sensor Networks (WSNs) suffers from low tracking accuracy and lack of reliability when a target cannot be detected by a scheduled sensor. To achieve better better tracking performance multiple sensors are used which consume high energy. Tracking accuracy, reliability, and energy consumed are affected by the continuous sensing. In this paper, an optimized energy-efficient multisensor scheduling scheme is proposed for collaborative target tracking in WSNs. Simulation results shows the comparison with the existing scheme and proposed scheme. Proposed scheme can achieve superior energy efficiency and tracking reliability while satisfying the tracking accuracy requirement. It is also robust to the uncertainty of the process noise.

To preserve the coverage of the sensing network for the maximum possible time is also a major goal in sensor network target tracking. And retransmission limits could also be taken into account for even better data accuracy.

2.6 Fatemeh Deldar and Mohammad Hossien Yaghmaee “Energy Efficient Prediction-based Clustering Algorithm for Target Tracking in Wireless Sensor Networks” 2010 International Conference on Intelligent Networking and Collaborative Systems pp 315-318[14]

Nowadays energy efficiency has become a main challenge in wireless sensor networks (WSNs) and their applications. Target tracking is one of the most important in these applications. In this paper the authors proposed an energy efficient prediction-based clustering algorithm for target tracking in WSNs. Trilateration algorithm attempts to decrease transmission distance between transmitter and receiver nodes and decrease the number of transmitted packets. Also proposed an algorithm which uses a prediction-based method. Prediction-based methods, with prediction the target trajectory and its next location, only activate

special nodes of network for tracking and rest of nodes remain in sleep mode for energy saving. Simulation results show that the Trilateration algorithm has better performance in energy efficiency from other prediction-based methods which leads to higher lifetime.

2.7 George K. Atia, Venugopal V. Veeravalli and Jason A. Fuemmeler "Sensor Scheduling for Energy-Efficient Target Tracking in Sensor Networks" on IEEE Transactions on Mobile Computing 2011[17]

In this paper the authors had studied the problem of tracking an object moving randomly through a network of wireless sensors. Their objective is to devise strategies for scheduling the sensors to optimize the tradeoff between tracking performance and energy consumption. They cast the scheduling problem as a Partially Observable Markov Decision Process (POMDP), where the control actions correspond to the set of sensors to activate at each time step. Using a bottom-up approach, they consider different sensing, motion and cost models with increasing levels of difficulty. At the first level, the sensing regions of the different sensors do not overlap and the target is only observed within the sensing range of an active sensor. Then, they consider sensors with overlapping sensing range such that the tracking error, and hence the actions of the different sensors, are tightly coupled. Finally, they consider scenarios wherein the target locations and sensors' observations assume values on continuous spaces. Exact solutions are generally intractable even for the simplest models due to the dimensionality of the information and action spaces. Hence, they devise approximate solution techniques. In some cases, the lower bounds can be derived on the optimal tradeoff curves. The generated scheduling policies, albeit suboptimal, often provide close-to-optimal energy-tracking tradeoffs.

3. MULTI-TARGET TRACKING

3.1 Joint Sensing

In this paper, it is assumed that each ultrasonic sensor installs the sound wave emitter and receiver and all the sensors in the network are homogeneous and time synchronized.

Normally an ultrasonic sensor adopts the active sensing mechanism where the sensor emits sound wave and measures the reflected echo from the target. The Time Of Flight (TOF) is converted into range information towards the target. Sensors adopt a simplified cone shape detection region model for a typical ultrasonic sensor, where one ultrasonic sensor 'i' is characterized by its location (X_{si}, Y_{si}) , orientation Θ_i , detection angle α , and detection range d . The TOF equals to the round trip time of the wave from the emitting sensor to the target and then back to the emitting sensor, which corresponds to the round trip distance of the sound wave that is bounded by $2d$.

The target can be jointly sensed by two sensors, if the following joint sensing conditions are satisfied:

1. The target is within the detection angles of both sensors;
2. The sum of distances from the target to the sensors is less than $2d$;
3. The two sensors are not within line of sight with each other (i.e., not within the detection angle of each other).

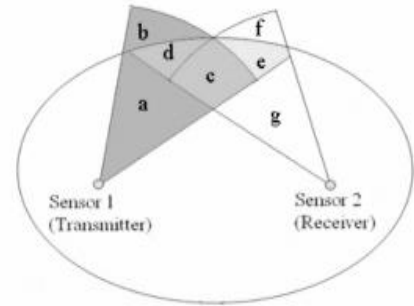


Figure 3.1 Joint sensing region

According to the above joint sensing conditions, no matter which sensor in these two sensors is the emitter, the signals can be received by the other sensor.

As an example, Fig. 3.1 shows the joint sensing region of sensors 1 and 2, when sensor 1 is the emitting sensor and sensor 2 is the receiving sensor. The ellipse consists of all points where the sum of its distances to sensor 1 and sensor 2 are $2d$. The target must be inside this ellipse if sensor 1 and sensor 2 can jointly sense the target.

In Figure 3.1, areas a and b can only be sensed by sensor 1 individually, as any point in area a is not in the detection angle of sensor 2 (i.e., not satisfy joint sensing condition 1) and the sum of the distances from any point in area b to sensor 1 and sensor 2 is larger than $2d$ (i.e., not satisfy joint sensing condition 2). Areas c, d, and e can be jointly sensed by sensor 1 and sensor 2 as any point in them satisfies the three joint sensing conditions.

The target located in area e can also be jointly sensed, which indicates that joint sensing can increase the detection region of individual sensors. In addition, if the target is located in area c or d, it can be obtained two sensor measurements, one is the distance from sensor 1 to the target, and the other one is the sum of the distances from sensor 1 to the target and from the target to sensor 2.

3.2 Adaptive Scheduling

A serious problem in WSN of active sensors is the inter-sensor interference (ISI) when nearby ultrasonic sensors emit sound wave simultaneously. Such interference will result in erroneous sensor readings and must be dealt with properly. ISI also introduces a new technological constraint in the design and implementation of a WSN. In this paper, we assume the WSN is deployed in a small area where the sensor nodes are in the interference range of each other, and only single target tracking is considered. To avoid ISI, at each time step, only one emitting sensor will be scheduled and the other sensors will participate in joint sensing with the scheduled emitting sensor. Periodic sensor scheduling is used where the time is divided into periodic cycles. Within a cycle, a predefined duration (called time slot) is assigned for each ultrasonic sensor for sensing, during which it can work properly without interference from other sensors. A critical drawback of periodic sensor scheduling is that detection may be missed when a scheduled sensor can not generate effective joint sensing measurements, which results in lower tracking accuracy.

To overcome the above drawback of period sensor scheduling, we introduce the adaptive sensor scheduling to select the emitting sensor for the next time step according to the predicted target location and the sensing region of the sensors.

3.3 Collaborative Sensing

In this paper, collaborative sensing is used to stand for joint sensing and the joint sensing enabled adaptive sensor scheduling. Either centralized or distributed target tracking structure can be adopted, depending on the fusion centre being the centralized management centre or the scheduled sensor. At each time step, the scheduled sensor emits the sound wave and all other sensor nodes that can perform joint sensing with the emitting sensor will collect the measurements and forward the measurements to the fusion centre. The fusion centre will run EKF to give updates of the state estimation using the new measurements and schedule the emitting sensor for the next time step. Then it will inform the scheduled sensor to perform the emitting operation in the next time step, together with the state estimation and covariance matrix information in the distributed structure. We assume that the fusion centre knows the location and orientation of each sensor. In the distributed structure, this means that each sensor knows such information of each node because each sensor is possible to be the fusion centre. Different measures can be used as the performance indices to select the emitting sensor, including the joint sensing detection probability, tracking accuracy, and energy efficiency. However, to calculate these performance indices under the joint sensing mechanism is not an easy task. For simplification and easy to compare with individual sensing scheme, in this paper, we schedule the emitting sensor according to the individual sensor detection probability. Due to the uncertainties in the target motion model such as the target maneuvering, even using adaptive sensor scheduling, it is still possible that the scheduled sensor can not detect the target. If this happens, the fusion centre will use the predicted state and its covariance matrix as the estimation result.

In this paper, the emitting sensor is selected as the sensor with the maximal detection probability for individual sensing. After the emitting sensor is selected and activated for emitting wave, for individual sensing scheme only the emitting sensor can take the measurement whereas for the joint sensing scheme, multiple sensors can take the measurements simultaneously.

Different measures can be used as the performance indices to select the emitting sensor, including the joint sensing detection probability, tracking accuracy, and energy efficiency. For each time step, energy consumption happens mainly in the following operations:

- 1) Sensing by sensors;
- 2) transmitting/receiving measurement data from sensors to the cluster head;
- 3) broadcasting/receiving by the current cluster head and sensors in the next cluster.

Sensor Node Placement

During the design phase of WSNs, the designer knows the number of sensor nodes, 100, which are deployed in a given field in either random or deterministic fashion. A circular field with radius R is considered in the experiments. In this section to introduce three nodes deployment strategies together with their characteristics. 16 Sensors are taken to track the targets. The area of targets will be available within the boundary of 1500*1500 square meters. Each sensor senses 150 square meters approximately. The entire sensor senses each and every part of the taken area. One base node is placed outside the taken area. Base node collects the information about the targets.

Target Estimation:

The model of human motion dynamics and in Cartesian coordinates provides the basis for filtering and smoothing the sensor data. Target position data may then be used for camera

control or for intelligent room applications. The target locations are identified and the collected information (X and Y co-ordinates) are passed to the base node. If the targets are not in the specified the sensors goes to the sleeping mode. The sensor does not emit energy.

4. RESULTS & DISCUSSION

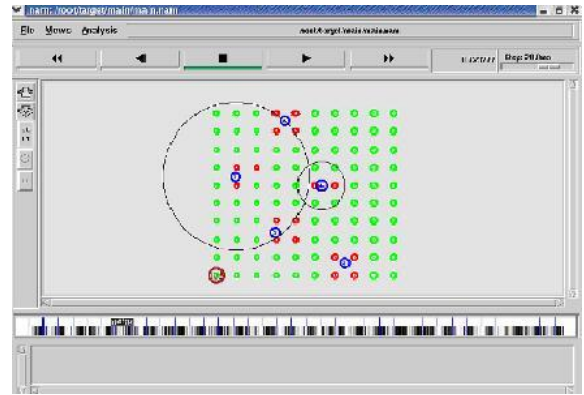


Figure 4.1 Sensing region of Cluster Model

The figure 4.1 shows the result of multi-target tracking in wireless sensor networks. Red colored sensors are sensing the targets. Green colored sensors shows that it is in the sleeping mode for saving energy.

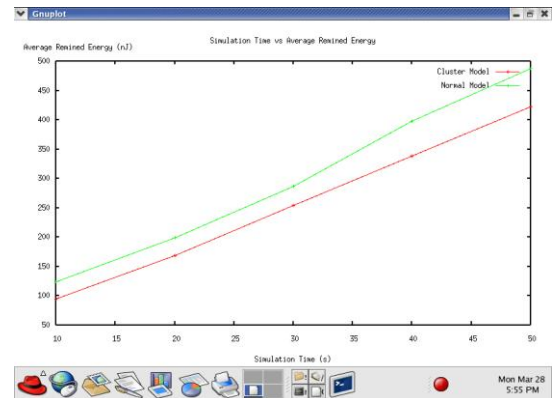


Figure 4.2. Average remained energy in cluster and normal model

Energy consumption is very high in normal model than cluster model. Cluster model uses maximum 4 sensors to track targets as shown in Figure 4.1. But Normal model uses all the sensors to track targets. All the sensors emit energy to find targets in normal model. Figure 4.2 shows comparison of energy consumed in normal model and cluster model.

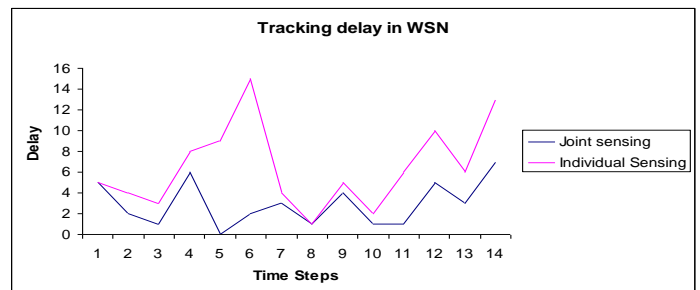


Figure 4.3 Tracking delay for adaptive sensor scheduling

The evolutions of tracking errors, i.e., the IQ, are shown in Figure. 4.3. The gain of the Joint Sensing is observed. The tracking delay for Joint Sensing and individual tracking are traced. The Joint Sensing gives a significant improvement in accuracy for tracking the targets

5. CONCLUSIONS

The scheme increases the detection region of an individual sensor and saves the energy of a sensor by sleeping mode. Proposed Algorithm finds maneuvering targets and multi-targets by saving energy. It is shown by simulations that the IQ of the WSN can be improved significantly using joint sensing. The proposed system supports to reduce the time needed to track the multi-targets. Future research issues include sensor scheduling for real test-bed development and to reduce the error rate. Several issues needed further enhancement in the proposed techniques.

6. REFERENCES

- [1] C. Bisdikian, "On Sensor Sampling and Quality of Information: a Starting Point," in Proc. of IEEE PERCOM Workshops, March 2007, pp. 279 - 284.
- [2] L. Chen, B.K. Szymanski, I.W. Branch, "Quality-Driven Congestion Control for Target Tracking in Wireless Sensor Networks," 5th IEEE International Conference on Mobile Ad Hoc and Sensor Systems (MASS 2008), Sept-Oct 2008, pp. 766 - 771.
- [3] Y. K. Toh, W. Xiao, and L. Xie, "A Wireless Sensor Network Target Tracking System with Distributed Competition based Sensor Scheduling," the third International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP 2007), Dec 2007, pp. 257-262.
- [4] Tolstikov, W. Xiao, I. Biswas, S. Zhang, and C. K. Tham, "Information Quality Management in Sensor Networks based on the Dynamic Bayesian Network Model," the third International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP 2007), Dec 2007, pp. 751-756.
- [5] J. Wang, Y. Liu, and S. K. Das, "Improving Information Quality of Sensory Data through Asynchronous Sampling," the First International Workshop on Information Quality and Quality of Service for Pervasive Computing (IQ2S 2009) in PerCom 2009, March 2009, pp. 1-6.
- [6] F. Zhao, I. Liu, I. Liu, L. Guibas, and I. Reich, "Collaborative Signal and Information Processing: an Information Directed Approach." Proc. IEEE, vol. 91, Aug. 2003, pp. 1199-1209.
- [7] J. Lin, W. Xiao, F. Lewis, and L. Xie, "Energy Efficient Distributed Adaptive Multi-Sensor Scheduling for Target Tracking in Wireless Sensor Networks," IEEE Transactions on Instrumentation and Measurement, vol. 58, Jun. 2009, pp. 1886-1896.
- [8] W. Xiao, J. K. Wu, L. Shue, Y. Li, and L. Xie, "A Prototype Ultrasonic Sensor Network for Tracking of Moving Targets," the 1st IEEE Conference on Industrial Electronics and Applications (ICIEA 2006), May 2006, pp. 1511-1516.
- [9] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, "Estimation with Applications to Tracking and Navigation". New York: John Wiley & Sons, 2001.
- [10] Wendong Xiao, Lihua Xie, Jianfeng Chen, and Louis Shue "Multi-Step Adaptive Sensor Scheduling for Target Tracking in Wireless Sensor Networks" ICASSP 2006, pp. 705 -708.
- [11] Sen Zhang , Wendong Xiao , Marcelo H Ang Jr , Chen Khong Tham "IMM Filter Based Sensor Scheduling for Maneuvering Target Tracking in Wireless Sensor Networks" ISSNIP 2007 pp. 287 – 292.
- [12] Yousef E. M. Hamouda and Chris Phillips "Metadata-Based Adaptive Sampling for Energy-Efficient Collaborative Target Tracking in Wireless Sensor Networks" 2010 10th IEEE International Conference on Computer and Information Technology (CIT 2010) pp 313-320
- [13] Yan-Xiao Li, Le-Bin Lu and Dong-Yang Liu "Research on Battlefield Target tracking in Wireless Sensor Networks" on 978-1-4244-6977-2/10/ 2010 IEEE
- [14] Fatemeh Deldar and Mohammad Hossien Yaghmaee "Energy Efficient Prediction-based Clustering Algorithm for Target Tracking in Wireless Sensor Networks" 2010 International Conference on Intelligent Networking and Collaborative Systems pp 315-318
- [15] Vaidehi.V, S.Vasuhi, K. Sri Ganesh, C. Theanammai, Naresh Babu N T, N Uthiravel, P.Balamuralidhar and Grish Chandra "Person Tracking Using Kalman Filter in WirelessSensor Network" on ICoAC 2010 pp 60-65
- [16] Dan Liu, Nihong Wang and Yi An "Dynamic Cluster Based Object Tracking Algorithm in WSN" 2010 Second WRI Global Congress on Intelligent Systems pp 397-399
- [17] George K. Atia, Venugopal V. Veeravalli and Jason A. Fuemmeler "Sensor Scheduling for Energy-Efficient Target Tracking in Sensor Networks" on IEEE TRANSACTIONS ON MOBILE COMPUTING 2011
- [18] Wendong Xiao and Chen Khong Tham and Sajal K. Das "Collaborative Sensing to Improve Information Quality for Target Tracking in Wireless Sensor Networks" on 978-1-4244-5328-3/10 IEEE 2010 pp 99-104
- [19] Dan Liu, Nihong Wang and Yi An "Dynamic Cluster Based Object Tracking Algorithm in WSN" 2010 Second WRI Global Congress on Intelligent Systems pp 397-399
- [20] Supreet Kaur Sarna and Mukesh Zaveri "EATT: Energy Aware Target Tracking for Wireless Sensor Networks Using TinyOS" on 978-1-4244-5540-9/10 IEEE 2010 pp 187-19