Global Journal of Research in Engineering
Volume 11 Issue 4 Version 1.0 April 2011
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
ISSN: 0975-5861

Online Sensor Collaboration to Achieve Quality of Service Requirements in Wireless Sensor Networks

By Archana Aravind, K.P.Sampoornam

Abstract- Wireless Sensor networks are currently being employed in a variety of applications ranging from medical to military, and from home to industry. Wireless Sensor Networks and Applications aims to provide a reference tool for the increasing number of scientists who depend upon reliable sensor networks. A fundamental challenge for these wireless sensor networks is to meet stringent Quality-of-Service requirements including high target detection probability, low false alarm rate, and bounded detection delay. This paper present a new formulation for the problem of target detection based on a novel two-phase detection approach .A near-optimal movement scheduling algorithm is developed that minimizes the expected moving distance of mobile sensors . It exploits reactive mobility to improve the target detection performance of moving targets in wireless sensor networks. In this approach, mobile sensors collaborate with static sensors and move reactively to achieve the required detection performance. Specifically, mobile sensors initially remain stationary and are directed to move toward a possible target only when a detection consensus is reached by a group of sensors.

Keywords: Wireless Sensor Networks (WSNs), Data fusion, Value fusion.

Classification: GJCST Classification: C.2.1, C.2.2

ONLINE SENSOR COLLABORATION TO ACHIEVE QUALITYOF SERVICE REQUIREMENTS IN WIRELESS SENSOR NETWORKS

Strictly as per the compliance and regulations of:

Online Sensor Collaboration to Achieve Quality of Service Requirements in Wireless Sensor Networks

Archana Aravind[α], K.P.Sampoornam[Ω]

Abstract- Wireless Sensor networks are currently being employed in a variety of applications ranging from medical to military, and from home to industry. Wireless Sensor Networks and Applications aims to provide a reference tool for the increasing number of scientists who depend upon reliable sensor networks. A fundamental challenge for these wireless sensor networks is to meet stringent Quality-of-Service requirements including high target detection probability, low false alarm rate, and bounded detection delay. This paper present a new formulation for the problem of target detection based on a novel two-phase detection approach .A near-optimal movement scheduling algorithm is developed that minimizes the expected moving distance of mobile sensors . It exploits reactive mobility to improve the target detection performance of moving targets in wireless sensor networks. In this approach, mobile sensors collaborate with static sensors and move reactively to achieve the required detection performance. Specifically, mobile sensors initially remain stationary and are directed to move toward a possible target only when a detection consensus is reached by a group of sensors.

Keywords:-Wireless Sensor Networks (WSNs), Data fusion, Value fusion.

I. Introduction

A fundamental challenge for wireless sensor networks is to meet stringent Quality-of-Service requirements including high target detection probability, low false alarm rate, and bounded detection delay. In many applications, the target is mobile [1].Several challenges are faced in detecting moving targets. First, the accurate position of the moving target is often unknown in practice. Moreover, the signal attenuation characteristic of the moving target varies over time. Therefore, it is difficult to find the optimal solution that achieves the specific detection performance requirement. Basic idea to address this issue is to treat the moving target as a stationary target with conservative source energy estimate [1]. For a cluster, it considers the performance of detecting the moving target with source energy of s_0 in a region A that is around the surveillance spot. Time that the target is in A is longer than the required detection delay D. Denote $d_{i,max}$ as the maximum distance from sensor i to any point in A .Hence, the minimum energy received by sensor i when the target is in A, denoted by $s_{i,\min}$, is $s_{i,min} = S_0 w(d_{i,max})$.In recent years, wireless sensor networks have been deployed in a class of mission-critical applications such as target detection [2], object tracking [3], and security surveillance [4]. This paper exploits reactive mobility to improve the target detection performance of wireless sensor networks [1]. In this paper, sparsely deployed mobile sensors collaborate with static sensors and move in a reactive manner to achieve required detection performance. Specifically, mobile sensors remain stationary until a possible target is detected. The accuracy of the final detection decision will be improved after mobile sensors move toward the possible target position and achieve higher Signal-to-Noise Ratios. By taking advantage of such reactive mobility, a network can adapt to irregular and unpredictable spatiotemporal distribution of targets. Moreover, the sensor density required in a network deployment is significantly reduced because the sensing coverage can be reconfigured in an on-demand fashion. Several challenges must be addressed for utilizing the mobility of sensors in target detection. First, practical mobile sensors are only capable of slow-speed movement, which may lead to long detection delays. The typical speed of mobile sensor systems (e.g., Networked Infomechanical Systems [5], Packbot [6], and Robomote [7]) is about 0.2-2 m/s. Therefore, the movement of sensors must be efficiently scheduled in order to reduce detection latency. Second, the number of mobile sensors available in a network deployment is often much smaller than that of static sensors due to higher manufacturing cost. Hence, mobile sensors must effectively collaborate with static sensors to achieve the maximum utility. At the same time, the coordination among sensors should not introduce high overhead or significant detection delay. Third, the distance that mobile sensors move in a detection process should be minimized. Due to the high power consumption of locomotion, frequent movement will quickly deplete the battery of a mobile node. Although mobile sensors may

About [α]- PG scholar, K.S.R. College of Engineering, Tiruchengode, Tamil Nadu,
E-mail– devi.achu @gmail.com, Mob: +91 9790874615.
About [Ω] - Associate Professor, K.S.R. College of Engineering, Tiruchengode, TamilNadu
E-mail– ambu_swasti@yahoo.com, Mob: +91 9629377780.

April 2011

Global Journal of Research in Engineering Volume XI Issue IV Version I

recharge their batteries by moving to locations with wired power supplies, frequent battery recharging causes disruptions to network topologies. Finally, moving sensors lowers the stealthiness of a network, which is not desirable for many applications deployed in hostile environments like battlefields. In the two-phase detection approach, mobile sensors initially remain stationary and are directed to move toward a possible target only when a detection consensus is reached by all nearby sensors. Such a strategy allows mobile sensors to avoid unnecessary movement through the collaboration with static sensors. Scheduling algorithm also enables mobile sensors to locally control their movement and sensing. Thus both coordination overhead and detection delay are reduced significantly.

II. Sensor Measurement Model

Sensors perform detection by measuring the energy of signals emitted by the target. The energy of most physical signals (e.g., acoustic and electromagnetic signals) attenuates with the dist ance from the signal source. Suppose sensor i is x_i meters away from the target that emits a signal of energy s_o , the attenuated signal energy $e_s(x_i)$ at the position of sensor i is given by $e_s(x_i) = s_0 .\mathrm{w}(x_i)$ where $\mathrm{w}(x_i)$ is referred to as signal decay function satisfying $\mathrm{w}(0) = 1$ and $\mathrm{w}(\infty) = 0$.The $\mathrm{w}(.)$ is referred to as the signal decay function. In this paper, the two-dimensional polar coordinate system is adopted with the target position as the origin .As the signal decay model is isotropic and the detection scheme adopted in this paper is based on the signal energy, angular coordinate is omitted and thus, scalar x_i can be referred to as the position of sensor i. The sensor measurements are contaminated by additive random noise from environment, sensor hardware, and other affecting random phenomena. Depending on the hypothesis that the target is absent (H_0) or present (H_1), the energy measurement of sensor i , denoted by e_i, is given by

$$H_0: \ e_i = e_n,$$

$$H_1: \ e_i = e_s(x_i) + e_n$$

Where e_n is the energy of noise experienced by sensor i. In practice, an energy measurement at a sensor is often estimated by the arithmetic average over a number of samples during a sampling interval of T seconds. Suppose the number of samples in a sampling interval is K, the noise energy is given by $e_n = 1/k \sum_{j=1}^{k} v_j^2$ where v_j is the noise intensity when taking the j^{th} sample. We assume that the noise intensity v_j is independent and identically distributed.

III. Detection and Decision Fusion Model

Data fusion [8] is a widely used technique for improving the performance of detection systems. There exist two basic data fusion schemes, namely, value fusion and decision fusion. In value fusion [10], each sensor sends its raw energy measurements to the cluster head, which makes the detection decision based on the received energy measurements. Different from value fusion, decision fusion operates in a distributed manner as follows: Each sensor makes a local decision based on its measurements and sends its decision to the cluster head, which makes a system decision according to the local decisions. Due to its low overhead, decision fusion is preferred in the bandwidth-constrained wireless sensor networks. Moreover, decision fusion allows mobile sensors to locally control their movement and sensing. In this work, the majority rule is adopted due to its simplicity. Specifically, each individual sensor first makes a local detection decision (0 or 1) by comparing the energy measurement against a detection threshold, and reports its local decision to the cluster head. The cluster head makes the system decision by the majority rule, i.e., if more than half of sensors vote 1, the cluster head decides 1; otherwise, it decides 0.The detection performance is usually characterized by two metrics, namely, the false alarm rate (PF) and detection probability (PD) [8],[9],[10] .PF is the probability of making a positive decision when no target is present, and PD is the probability that a present target is correctly detected. .The optimal decision rule at sensor i is the Likelihood Ratio Test [8] in which sensor *i* compares its energy measurement with a detection threshold λ_i .Hence, the local false alarm rate and detection probability, denoted by, P_F^i *and* P_D^i,

$$P_F^i = Pr(e_i \geq \lambda_i \ I \ H_0) \ = Q\left(\frac{\lambda_i - \mu}{\sigma}\right),$$

$$P_D^i = Pr(e_i \geq \lambda_i \ I \ H_1) \ = Q\left(\frac{\lambda_i - \mu - e_s(x_i)}{\sigma}\right),$$

Where Q(.) is the complementary Cumulative Distribution Function of the standard normal distribution, i.e.,

$$\mathrm{Q(x)} = \int_{\mathrm{x}}^{+\propto} \frac{1}{\sqrt{2\mathrm{x}}} \mathrm{exp}(-\frac{\mathrm{t}^2}{2})\mathrm{dt}$$

IV. Mobility-Assisted Target Detection with Decision Fusion

This section formulates the problem. A two-phase detection approach is proposed and the problem is formally formulated in Section 3.1

a) Problem Formulation And Approach Overview

The detection performance requirement is characterized by a 3-tuple α,β,D> Specifically, for any target that appears at the surveillance spot: 1) the system false alarm rate is no higher than α 2) the system detection probability is no lower than β and 3) the expected detection delay is no longer than D. As a static network may not meet a stringent performance requirement, a two phase detection approach is utilized to meet the mobility of sensors as follows:

1. The target detection is carried out periodically and each detection cycle comprises two phases. The length of the detection cycle that can meet the requirement on detection delay is analyzed later in this section.
2. In the first phase, each sensor stays stationary and measures signal energy for a sampling interval T. It then makes a local decision by comparing against a predefined threshold. Each sensor reports its local decision to the cluster head, which makes a system decision according to the majority rule. If a positive system decision is made, the second phase is initiated; otherwise, the second phase is skipped, and the cluster yields a negative final decision for this cycle.
3. In the second phase, each sensor continuously measures signal energies. Note that each signal energy measurement is gathered for a sampling interval of T. Mobile sensors simultaneously move toward the surveillance spot according to their movement schedules. A sequential fusion like procedure is adopted at each sensor to make its local decision. Specifically, after each sampling interval, if the sum of signal energies measured by a sensor in this phase exceeds predefined threshold, the sensor makes a positive local decision and terminates its second-phase detection; otherwise, it continues to sense. When the maximum time duration of the second phase is reached, a sensor makes a negative local decision if its cumulative signal energy is still below the threshold. If a mobile sensor makes a positive local decision, it also terminates its movement no matter whether its movement schedule is completed
4. As soon as enough local decisions for the second phase detection are received to reach a majority consensus, a positive final detection decision for this cycle is made and the cluster enters the next detection cycle. After the end of the second phase, the mobile sensors shared by multiple clusters may need to move back to their original positions if such movement causes the detection performances of other clusters to be lower than the requirements. Otherwise, these shared mobile sensors stay at the new positions to avoid the energy consumed in moving back.

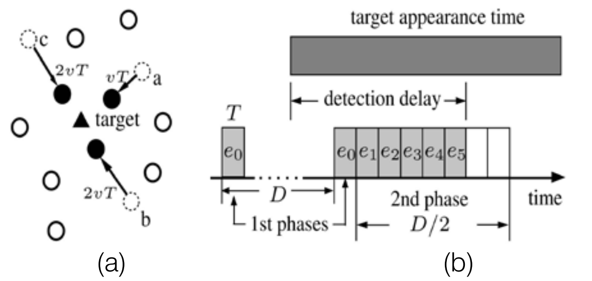

Fig1: The illustration of the two-phase detection. (a) Spatial view: void and solid circled represent static and mobile sensors, respectively. The moving distance of a mobile sensor is multiple of vT. (b) Temporal view: the figure draws two detection cycles for a sensor. In the first cycle, the second phase is not initiated as the target is absent .In the second cycle, the sensor terminates its second-phase detection in advance as $\sum_{j=1}^{5} e_j$ exceeds the threshold, although maximum seven sampling intervals are allowed

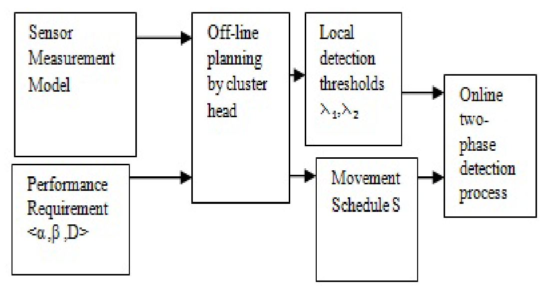

Fig.2.Overview of the approach

Such a two-phase approach has several advantages:

1) Unnecessary movement of mobile sensors is avoided, as mobile sensors start to move only after the first-phase detection produces a positive decision

2) The sequential detection strategy allows each mobile sensor to locally control its sensing and moving according to its movement schedule, which avoids inter node coordination overhead. Therefore, only the communication between the cluster head and each member sensor is required

3) Moreover, as a sensor can terminate its detection and movement schedule in advance if it has enough cumulative signal energy to make a positive decision, the delay of reaching a consensus and the locomotion energy consumption can be reduced

V. Results and Discussion

Sensor Movement Scheduling Algorithm is developed and QOS requirements are measured. The performance of Sensor Movement Scheduling Algorithm is compared with greedy algorithm and set of simulations evaluates the basic performance of mobility-assisted detection model and the effectiveness of Movement Scheduling algorithm.

Fig.3 shows the number of nodes detected by Movement Scheduling Algorithm and Greedy Algorithm when the detection probability varies from 0 to 10 %.

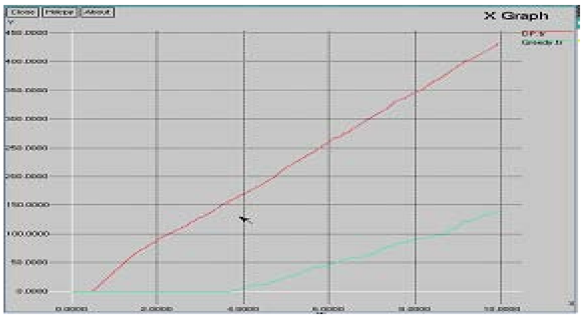

Fig.3. The number of nodes versus Detection Probability

In Greedy Algorithm Probability detection is poor. By means of Greedy Algorithm only 140 nodes were detected but by Sensor Movement Scheduling Algorithm 450 nodes were detected with highest probability 10%

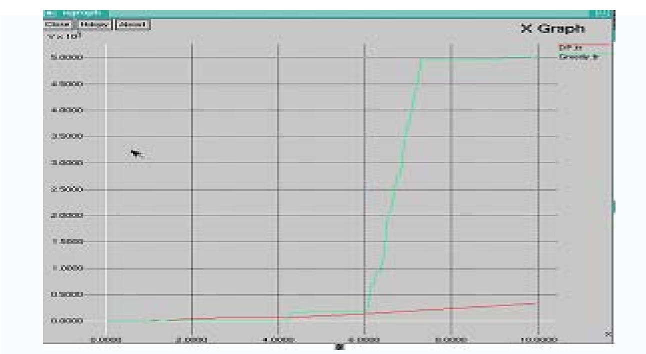

Fig.4. The number of scheduled moves versus Requested PD

Fig.4 shows the total number of moves in the schedules found by different algorithms when the requested detection probability varies. In Movement Scheduling Algorithm with less number of moves the requested PD is achieved

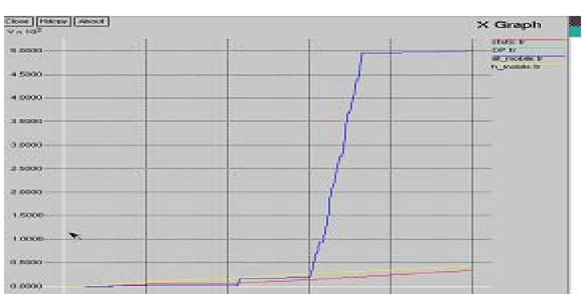

Fig.5. False alarm rate versus Detection probability

Fig.5 shows the receiver operating characteristics for different number of mobile sensors. Under each false alarm rate bound, the movement schedule of mobile sensors is computed to maximize the system detection probability. System detection performance increases significantly with the number of mobile sensors

VI. Conclusion

In this paper reactive mobility is employed to improve the detection performance of moving targets in wireless sensor networks A two phase detection approach is proposed in which mobile sensors collaborate with static sensors and move reactively to achieve the required detection performance. Sensor Movement Scheduling Algorithm is developed that minimizes the expected moving distance of mobile sensors Simulations shows that a small number of mobile sensors can significantly improve the system detection performance

References Références Referencias

1. Rui Tan, Guoliang Xing, Jianping Wang, Hing Cheung So," Exploiting Reactive Mobility for Collaborative Target Detection in Wireless Sensor Networks", Ieee Transactions on Mobile Computing, Vol.9, N0.3, March 2010
2. D. Li, K. Wong, Y.H. Hu, and A. Sayeed, "Detection, Classification and Tracking of Targets in Distributed Sensor Networks," IEEE Signal Processing Magazine, vol. 19, no. 2, pp. 17-29, Mar. 2002.
3. F. Zhao, J. Shin, and J. Reich, "Information-Driven Dynamic Sensor Collaboration for Tracking Applications," IEEE Signal Processing Magazine, vol. 19, no. 2, pp. 61-72, Mar. 2002.
4. T. He, S. Krishnamurthy, J.A. Stankovic, T. Abdelzaher, L. Luo, R.Stoleru, T. Yan, L. Gu, J. Hui, and B. Krogh, "Energy-Efficient Surveillance System Using Wireless Sensor Networks," Proc. MobiSys, 2004.
5. R. Pon, M.A. Batalin, J. Gordon, A. Kansal, D. Liu, M. Rahimi, L.Shirachi, Y. Yu, M. Hansen, W.J. Kaiser, M. Srivastava, G.Sukhatme, and D. Estrin, "Networked Infomechanical Systems: A Mobile Embedded Networked Sensor Platform," Proc. Int'l Symp. Information Processing in Sensor Networks (IPSN '05), 2005.
6. A.A. Somasundara, A. Ramamoorthy, and B. Srivastava, "Mobile Element Scheduling with Dynamic Deadlines," IEEE Trans. Mobile Computing, vol. 6, no. 4, pp. 395-410, Apr. 2007.
7. K. Dantu, M. Rahimi, H. Shah, S. Babel, A.Dhariwal, and G.S Sukhatme, "Robomote: EnablingMobilityin Sensor Networks,Proc. Int'l Symp. Information Processing in Sensor Networks (IPSN'05), 2005.

8. P. Varshney, Distributed Detection and Data Fusion. Springer-Verlag, 1996.
9. R. Niu, P.K. Varshney, M. Moore, and D. Klamer, “Decision Fusion in a Wireless Sensor Network with a Large Number of Sensors,” Proc. Int’l Conf. Information Fusion (FUSION), 2004.
10. T.Clouqueur, K.K.Saluja and. Ramanathan, “Fault Tolerance in Collaborative Sensor Networks for Target Detection,” IEEE Trans.Computers, vol. 53, no. 3, pp. 320-333, Mar. 2004.

This page is intentionally left blank