

INGENIOUS WIRELESS SENSOR NETWORK APPLICATIONS USING ADVANCED DATA FUSION TECHNIQUES

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ABSTRACT

The data fusion is an emerging technology. An efficient data fusion algorithm plays an important role in tracking for moving objects over WSS (wireless sensor system) deployments in order to track the objects accurately. Accuracy in object tracking is mainly dominated by the prediction for those moving targets by filtering and refining the results from wireless mobile sensors deployed in WSS environment. Rapid evolution of microprocessors, advanced sensors, and new techniques has led to new capabilities to combine data from multiple sensors for improved inferences. Applications of data fusion range from battlefield surveillance and automatic target recognition for smart weapons. Data fusion models that fuse noisy measurements of multiple sensors. Deriving the scaling laws between coverage, network density, and signal-to-noise ratio (SNR). Optimal fusion range that maximizes the coverage of regular networks increases with network density.

Keywords: Wireless sensor, Fusion techniques & DISC Model

1. INTRODUCTION

Wireless communication is an application of science and technology that has come to be vital for modern existence. From the early radio and telephone to current devices such as mobile phones and laptops, accessing the global network has become the most essential and indispensable part of our lifestyle. Wireless communication is an ever-developing field, and the future holds many possibilities in this area. One expectation for the future in this field is that, the device can be developed to support communication with higher data rates and more security. Research in this area suggests that a dominant means of supporting such communication capabilities will be through the use of Data Fusion.

The more modern networks are bi-directional, also enabling control of sensor activity. The development of wireless sensor networks was motivated by military applications such as battlefield surveillance; today such networks are used in many industrial and consumer applications, such as industrial process monitoring and control, machine health monitoring.

Multidimensional data processing is known as Data-Fusion. This information may be partly redundant but certainly not enough. The main strategy of Data-Fusion is to process the actual multi-dimensional measurement data, given in the measurement vector, at once, and find the optimal combination to produce the best possible state estimate.

A sensor network comprises of sensor nodes and a base station. Each sensor node is battery powered and equipped with integrated sensors, Data processing capabilities, Short- range radio communications. Due to their limited power and shorter communication range, sensor nodes perform in-network data fusion. A data fusion node collects the results from multiple nodes. It fuses the results with its own based on a decision criterion. Sends the fused data to another node or base station. Sensory data comes from multiple sensors of different modalities in distributed locations. The smart environment needs information about its surroundings as well as about its internal workings.

Hence, Wireless networks have significant impact on the world. Specifically, telecommunication wireless network has made significant impacts. As these networks become more mobile, and move into remote locations, the need for battery operated devices running energy efficient wireless protocols increases. Energy densities of batteries have only doubled every 5 to 20 years, depending on the particular chemistry

of the battery. Prolonged refinement of any given chemistry yields diminishing returns. For this reason, energy conservation in wireless protocols will continue to be a critical issue in the foreseeable future.

Wireless networks that are commercially available today have a protocol that includes designs to increase power efficiency. Many of the newer energy efficient protocols take concepts utilized in these protocols and improve them or tweak them for networks designed for a slightly different purpose.

All wireless networks benefit from lower energy usage. Each new generation of wireless product expands the accessibility of telecommunication networks. The advantages of the Data Fusion techniques are to reduce the traffic load and to conserve the energy of sensors.

2. LITERATURE SURVEY

ENERGY EFFICIENT SURVEILLANCE SYSTEM

“Energy-efficient surveillance system using wireless sensor networks,” T. He, S. Krishnamurthy, J. A. Stankovic, T. Abdelzaher, L. Luo, R. Stoleru, T. Yan, L. Gu, J. Hui, and B. Krogh [2]. The focus of surveillance missions is to acquire and verify information about enemy capabilities and positions of hostile targets. Hence, the ability to deploy unmanned surveillance missions, by using wireless sensor networks, is of great practical importance for the military. Because of the energy constraints of sensor devices, such systems necessitate an energy-aware design to ensure the longevity of surveillance missions. Solutions proposed recently for this type of system show promising results through simulations. Energy consumption is narrowly accounted for within a single protocol.

The system allows a group of cooperating sensor devices to detect and track the positions of moving vehicles in an energy efficient and stealthy manner. We can trade off energy awareness and surveillance performance by adaptively adjusting the sensitivity of the system. We evaluate the performance on a network of 70 MICA2 motes equipped with dual-axis magnetometers. Our results show that our surveillance strategy is adaptable and achieves a significant extension of network lifetime.

“Coverage by randomly deployed wireless sensor networks,” IEEE Trans. Inf. Theory, P.-J. Wan and C.-W. Yi [4]. One of the main applications of wireless sensor networks is to provide proper coverage of their deployment regions. A wireless sensor network covers its deployment region if every point in its deployment region is within the coverage ranges of at least sensors.

It assumes that the sensors are deployed as either a Poisson point process or a uniform point process in a square or disk region, and study how the probability of the coverage changes with the sensing radius or the number of sensors. Our results take the complicated boundary effect into account, rather than avoiding it by assuming the toroidal metric as done in the literature.

HABITAT MONITORING

“Wireless sensor networks for habitat monitoring,” in Proc. ACM WSNA, A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson [3]. Habitat and environmental monitoring represent a class of sensor network applications with enormous potential benefits for scientific communities and society as a whole. The connection with the immediate physical environment allows each sensor to provide localized measurements and detailed information that is hard to obtain through traditional instrumentation. Increased power efficiency gives applications flexibility in resolving fundamental design tradeoffs. The computing and networking capabilities allow sensor networks to be reprogrammed or retasked after deployment in the field. Nodes have the ability to adapt their operation over time in response to changes in the environment, the condition of the sensor network itself, or the scientific endeavor.

Many research groups have proposed using WSNs for habitat and microclimate monitoring. Although there are many interesting research problems in sensor networks, computer scientists must work closely with biologists to create a system that produces useful data while leveraging sensor network research for robustness and predictable operation.

“Unreliable sensor grids: Coverage, connectivity and diameter,” in Proc. IEEE INFOCOM, S. Shakkottai, R. Srikant, and N. Shroff [5]. Consider an unreliable wireless sensor grid network with n nodes placed in a square of unit area. We are interested in the coverage of the region and the connectivity of the network. We first show that the necessary and sufficient conditions for the random grid network to cover the unit square region as well as ensure that the active nodes are connected, even if each node is highly unreliable and the transmission power is small, we can still maintain connectivity with coverage. We also

show that the diameter of the random finally, we derive a sufficient condition for connectivity of the active nodes (without necessarily having coverage). If the node success probability $p(n)$ is small enough.

“Stochastic event capture using mobile sensors subject to a quality metric,” in Proc. ACM MobiCom, [11]. Mobile sensors cover more area over a fixed period of time than the same number of stationary sensors. However, the quality of coverage achieved by mobile sensors depends on the velocity, mobility pattern, number of mobile sensors deployed and the dynamics of the phenomenon being sensed. The gains attained by mobile sensors over static sensors and the optimal motion strategies for mobile sensors are not well understood. In this paper we consider the following event capture problem: The events of interest arrive at certain points in the sensor field and disappear according to known arrival and departure time distributions. An event is said to be captured if it is sensed by one of the mobile sensors before it fades away. Analyze how the quality of coverage scales with velocity, path and number of mobile sensors. Characterize cases where the deployment of mobile sensors has no advantage over static sensors and find the optimal velocity pattern that a mobile sensor should adopt.

Algorithms for two motion planning problems: (i) for a single sensor, what is the sensor trajectory and the minimum speed required to satisfy a bound on the event loss probability, and (ii) for sensors with fixed speed. For the minimum sensor problem, the number of sensors used is within a factor of two of the optimal solution. For the case where the events occur at arbitrary points on a plane, we present heuristic algorithms for the above motion planning problems and bound their performance with respect to the optimal.

“Vehicle classification in distributed sensor networks,” J. Parallel Distrib. Comput., [7]. The task of classifying the types of moving vehicles in a distributed, wireless sensor network is investigated. Specifically, based on an extensive real world experiment, we have compiled a data set that consists of 820 MByte raw time series data, 70 MByte of preprocessed, extracted spectral feature vectors, and baseline classification results using the maximum likelihood classifier. The purpose of this paper is to detail the data collection procedure, the feature extraction and pre-processing steps, and baseline classifier development.

“Optimal data fusion in multiple sensor detection systems,” IEEE Trans. Z. Chair and P. Varshney [7]. Due to limitations in channel capacity, the sensors transmit their decision instead of raw data. In addition to their decisions, the sensors may transmit one or more bits of quality information. Data fusion in a central when the data that the fusion center receives consist of the decisions made by each sensor individually and independently from each other. They derive the optimal fusion rule for the likelihood ratio (LR) test. It turns out that the sufficient statistics for the LR test is a weighted average of the decisions of the various sensors with weights that are functions of the individual probabilities of false alarm PF and the probabilities of detection PD.

3. PROJECT DESCRIPTION

3.1 DATA FUSION

The data fusion techniques can significantly improve sensing coverage by exploiting the collaboration among sensors when several physical properties of the target signal are known. Advanced collaborative signal processing algorithms have been adopted by many existing WSNs, most previous analytical studies on sensing coverage are conducted based on the simplistic sensing models (e.g., the disc model) that do not capture the stochastic nature of sensing. In this paper, we attempt to bridge this gap by exploring the fundamental limits of coverage based on stochastic data fusion models that fuse noisy measurements of multiple sensors. We derive the scaling laws between coverage, network density, and signal-to-noise ratio (SNR). Moreover, data fusion can also reduce network density for regularly deployed networks and mobile networks where mobile sensors can relocate to fill coverage holes.

Recent years have witnessed the deployments of wireless sensor networks (WSNs) for many critical applications such as security surveillance, environmental monitoring, and target detection or tracking. Many of these applications involve a large number of sensors distributed in a vast geographical area. As a result, the cost of deploying these networks into the physical environment is high. A key challenge is thus to predict and understand the expected sensing performance of these WSNs. A fundamental performance measure of WSNs is sensing coverage that characterizes how well a sensing field is monitored by a network.

Many recent studies are focused on analyzing the coverage performance of large-scale WSNs a key challenge faced by the research on sensing coverage is the obvious discrepancy between the advanced information processing schemes adopted by existing sensor networks and the overly simplistic sensing

models widely assumed in the previous analytical studies. On the one hand, many WSN applications are designed based on collaborative signal processing algorithms that improve the sensing performance of a network by jointly processing the noisy measurements of multiple sensors. In practice, various stochastic data fusion schemes have been employed by sensor network systems for event monitoring, detection, localization, and classification.

3.1.1 DISC MODEL

The sensing region of a sensor is often modeled as a disc with radius r centered at the position of the sensor, where r is referred to as the sensing range. A sensor deterministically detects the targets within its sensing range. Although such a model allows a geometric treatment to the coverage problem, it fails to capture the stochastic nature of sensing. The inaccuracy of the disc sensing model, we plot the sensing performance of an acoustic sensor in the following figure using the data traces collected from a real vehicle detection experiment. In the experiment, the sensor detects moving vehicles by comparing its signal energy measurement against a threshold. The probability that the sensor detects a vehicle (denoted by PD) versus the distance from the vehicle. No clear cutoff boundary between successful and unsuccessful sensing of the target.

As the classical disc model deterministically treats the detection performance of sensors, existing results based on this model, cannot be readily applied to analyze the performance or guide the design of real-world WSNs. In this section, we extend the classical disc model based on the stochastic detection to capture several realistic sensing characteristics and study the (α, β) - coverage under the extended model.

In the probabilistic disc model, we choose the sensing range r such that: 1) the probability of detecting any target within the sensing range is no lower than β ; and 2) the false alarm rate is no greater than α . As the probabilistic disc model ignores the detection probability outside the sensing range of a sensor, the detection capability of a sensor under this model is lower than in reality. However, this model preserves the boundary of sensing region defined in the classical disc model. Hence, the existing results based on the classical disc model can be naturally extended to the context of stochastic detection.

Many sensor network systems have incorporated various data fusion schemes to improve the system performance. In the surveillance system the system false alarm rate is reduced by fusing the detection decisions made by multiple sensors. Advanced data fusion techniques have been employed in a number of algorithms and protocols designed for target detection, localization and classification. Despite the wide adoption of data fusion in practice, the performance analysis of large-scale fusion-based WSNs has received little attention. The covered region under the disc model is simply the union of all sensing discs. As a result, when a high level of coverage is required, a large number of extra sensors must be deployed to eliminate small uncovered areas surrounded by sensing discs.

The probabilistic disc model captures the stochastic nature of sensing, it has two similar major limitations as the classical disc model. First, as the disc model ignores the sensing capability outside the sensing range of a sensor, it cannot accurately quantify the real sensing performance of a sensor. Second, as the disc model does not exploit the collaboration among sensors, the existing analytical results based on the disc model may significantly underestimate the system sensing performance that a WSN can achieve. The above two results will be used as the baselines to study the impact of data fusion on coverage of random and regular networks

3.2 DATA FUSION MODEL

The stochastic signal detection based on multisensor data fusion. Early works focus on small-scale powerful sensor networks (e.g., several radars). Recent studies on data fusion have considered the specific properties of WSNs such as sensors spatial distribution limited sensing or communication capability, and sensor failure. These studies focus on analyzing the optimal fusion strategies that maximize the system performance of a given network. The fundamental limits of sensing coverage of WSNs that are designed based on existing data fusion strategies.

Data fusion architecture is developed, which includes the data collection level where the sensors are used while distributed on different platforms. The second level processing is called low-level processing includes the data association, data alignment, sensor registration, and identity and position fusion. The high-level processing includes the threat assessment, (SA) situation Assessment and sensor management.

As one of the most fundamental issues in WSNs, the coverage problem has attracted significant research attention. Previous works fall into two categories namely, coverage maintenance algorithms/protocols and theoretical analysis of coverage performance. These two categories are reviewed briefly as follows, respectively. Early work quantifies sensing coverage by the length of target's path where the accumulative observations of sensors are maximum or minimum. However, these works focus on devising algorithms for finding the target's paths with certain level of coverage.

Several algorithms and protocols are designed to maintain sensing coverage using the minimum number of sensors. However, the effectiveness of these schemes largely relies on the assumption that sensors have circular sensing regions and deterministic sensing capability. Several recent studies on the coverage problem have adopted probabilistic sensing models. The numerical results show that the coverage of a network can be expanded by the cooperation of sensors through data fusion. Analyzing the fundamental limits of coverage in WSNs, all of these studies aim to devise algorithms and protocols for coverage maintenance.

Recent works have revealed that sensor mobility to reduce network density in achieving coverage. In such a scheme, randomly distributed mobile sensors can relocate themselves to fill coverage holes in the initial network deployment. A sensor relocation strategy is proposed in to achieve full coverage with bounded moving distance of mobile sensors. In this paper, we extend the strategy to the data fusion model. The coverage of mobile WSNs with random sensor mobility has been studied based on the disc model. In this paper, we focus on quantifying the improvement of coverage in the mobile networks with limited sensor mobility due to data fusion.

Data fusion can improve the performance of detection systems by jointly considering the noisy measurements of multiple sensors. There exist two basic data fusion schemes namely, decision fusion and value fusion. In decision fusion, 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. The optimal decision fusion rule has been obtained.

In value fusion, each sensor sends its measurements to the cluster head, which makes the detection decision based on the received measurements. We focus on value fusion, as it usually has better detection performance than decision fusion. The optimal value fusion rule is to compare a weighted sum of sensors measurements, $\sum_i (S_i / \sigma_i) \cdot y_i$ to a threshold.

A sensor measurements contain both noise and signal energy, the weight S_i / σ_i , i.e., the SNR received by sensor i , is unknown. A practical solution is to adopt equal constant weights for all sensors measurements. Since the measurements from different sensors are treated equally, the sensors far away from the target should be excluded from data fusion as their measurements suffer low SNRs.

For any physical point p , the sensors within a distance of R meters from p form a cluster and fuse their measurements to detect whether a target is present at p . R is referred to as the fusion range, and $F(p)$ denotes the set of sensors within the fusion range of p . The number of sensors in $F(p)$ is represented by $N(p)$. A cluster head is elected to make the detection decision by comparing the sum of measurements reported by member sensors in $F(p)$ against a detection threshold T . Let Y denote the fusion statistic. If $Y \geq T$, the cluster head decides H_1 ; otherwise, it decides H_0 .

The detection of a target is inherently stochastic due to the noise in sensor measurements. The detection performance is usually characterized by two metrics namely, the false alarm rate (denoted by PF) and detection probability (denoted by PD). 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. In stochastic detection, positive detection decisions may be false alarms caused by the noise in sensor measurements.

In particular, although the detection probability can be improved by setting lower detection thresholds, the fidelity of detection results may be unacceptable because of high false alarm rates. Therefore, PF together with PD characterize the sensing quality provided by the network. For a physical point P , we denote the probability of successfully detecting a target located at P as $PD(P)$. Note that PF is the probability of making positive decision when no target is present, and hence is location-independent.

To extend the coverage of random networks under the classical disc model to (α, β) - coverage. Under both the classical and probabilistic disc models, a location is regarded as being covered if it is within at least one sensor's sensing range. Accordingly, the area of the union of all sensors' sensing ranges is regarded as being covered by the network. The coverage of random networks under the classical disc model has been extensively studied based on the stochastic theory.

Although the probabilistic disc model captures the stochastic nature of sensing, it has two similar major limitations as the classical disc model. First, as the disc model ignores the sensing capability outside the sensing range of a sensor, it cannot accurately quantify the real sensing performance of a sensor. Second, as the disc model does not exploit the collaboration among sensors, the existing analytical results based on the disc model may significantly underestimate the system sensing performance that a WSN can achieve. The above two results will be used as the baselines to study the impact of data fusion on coverage of random and regular networks respectively.

3.3 DATA FUSION ON COVERAGE OF RANDOM NETWORKS

Many mission-critical applications require a high level of coverage over the surveillance region. As an asymptotic case, full coverage is required, i.e., any target/event present in the region can be detected with a probability of at least β while the false alarm rate is below α . For random networks, a higher level of coverage always requires more sensors. Therefore, the network density for achieving full coverage is an important cost metric for mission-critical applications.

3.4 DATA FUSION ON COVERAGE OF REGULAR AND MOBILE NETWORKS

It has been shown that random network deployments can lead to undesirable overprovision of sensing coverage, i.e., many fully covered areas have redundant sensors. We will study the coverage of regular networks, in which sensors are deployed at grid points. Our analysis shows that the data fusion can still reduce the network density for achieving full coverage of regular networks. Recent works show that mobility can be introduced to trade with network density in achieving coverage. In such a scheme, randomly distributed mobile sensors relocate themselves to fill coverage holes in the initial network deployment. We will extend a relocation strategy proposed in to the data fusion model. Our analysis shows that data fusion results in lower network density without increasing the moving distance of mobile sensors.

3.5 LOCALIZATION ALGORITHM

Fusion range is an important design parameter of our data fusion model. As SNR received by sensor decays with distance from the target, fusion range lower bounds the quality of information that is fused at the cluster head. The above data fusion model is consistent with the fusion schemes. If more efficient fusion models are employed, the scaling laws proved in this still hold.

We assume that the target keeps stationary after appearance and the position of a possible target can be obtained through a localization algorithm. For instance, the target position can be estimated as the geometric center of a number of sensors with the largest measurements. Such a simple localization algorithm is employed in the simulations.

The localized position may not be the exact target position, and the distance between them is referred to as localization error. We assume that the localization error is upper-bounded by a constant. The localization error is accounted for in the following analyses. However, we show that it has no impact on the asymptotic results derived.

3.6 NETWORK CLUSTERING

Network clustering has become an important technique in different networking research areas. With good network clustering algorithm, we can design scalable and efficient routing protocols, enhance scalability and efficiency of large-scale distributed systems and resolve many critical networking issues. Network clustering is used to study the clustering features of AS-level Internet topology and a realistic topology model is designed based on the observed clustering features.

Network clustering can be performed in both centralized and distributed ways. Centralized network clustering is an offline procedure, in which complete network topology information is required. Thus, centralized clustering is usually used for small networks or off-line data analysis. For the large scale system distributed clustering techniques is used.

To design a good network clustering protocol, we must consider the following design criteria. First of all, as a natural requirement of network clustering, nodes in the same clusters should be highly connected, and less connected between clusters. Secondly, a good clustering protocol should control cluster size (or cluster diameter) well. Thirdly, the number of regular nodes should be minimized. Lastly, a good

distributed clustering protocol should take node dynamics into account, especially when the clustering targets are highly dynamic with frequent node entry and exit.

3.6.1 DYNAMIC CLUSTERING ALGORITHM

The data fusion model can be used for target detection as follows. The detection can be executed periodically or triggered by user queries. In a detection process, each sensor makes a snapshot measurement, and a cluster is formed by the sensors within the fusion range from the possible target to make a detection decision.

The cluster formation may be initiated by the sensor that has the largest measurement. Such a scheme can be implemented by several dynamic clustering algorithms. The fusion range R can be used as an input parameter of the clustering algorithm.

The communication topology of the cluster can be a multihop tree rooted at the cluster head. As the fusion statistic Y is an aggregation of sensors measurements, it can be computed efficiently along the routing path to the cluster head.

The tasks of an active cluster head include the following four steps:

- Broadcasting a packet that contains the energy and the extracted signature of the detected signal to sensors,
- Receiving replies from sensors,
- Estimating the location of the target based on replies, and
- Sending the result to the user.

3.7 SIMULATION AND EXPERIMENTAL RESULTS

In this simulation part we have done extensive simulations based on synthetic data to evaluate the coverage performance of a network.

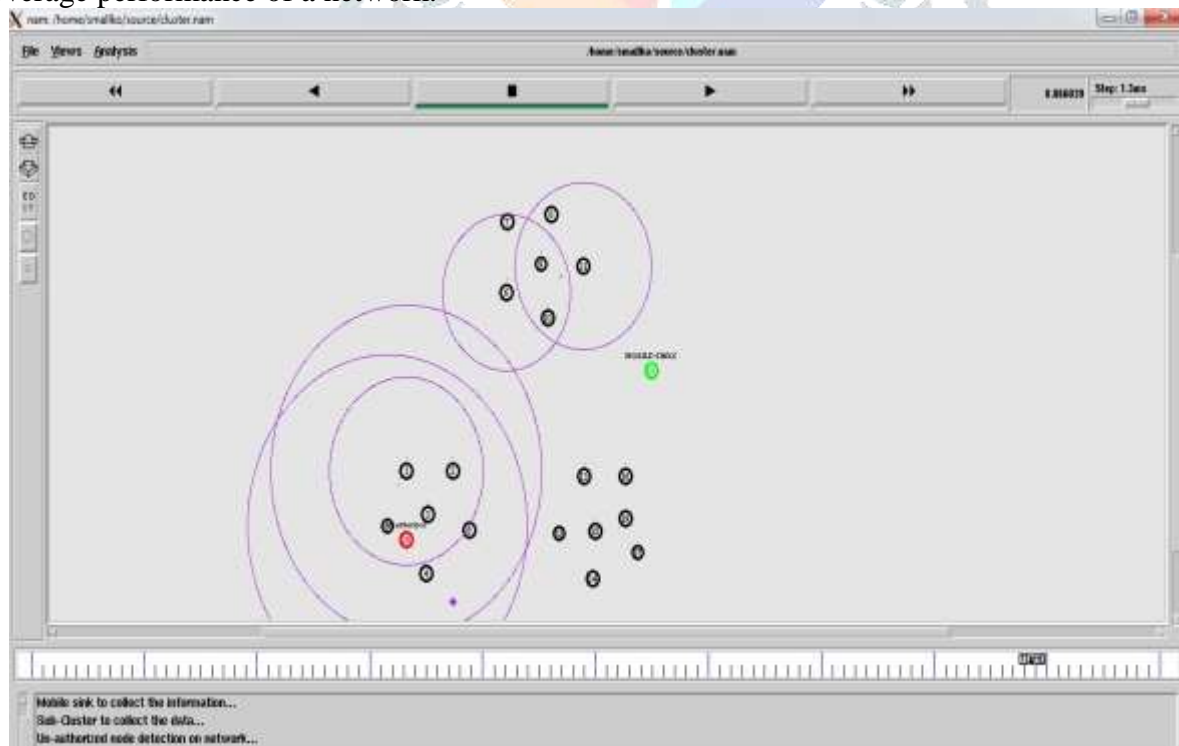


Fig: 1 Simulation using Network Simulator Tool

3.7.1 Simulation Results of Regular and Mobile Networks

The simulation results are shown when sensors are deployed at grid points. We have to measure the minimum network densities for achieving full coverage under disc and fusion models, respectively. For the fusion model, we numerically find the optimal fusion range that minimizes the network density for

achieving full coverage. We can see that the fusion model can reduce 100% of sensors compared to the disc model in a wide range of PSNRs, i.e., from 15 to 37 dB. The fusion model is more effective in the case of low PSNRs,



Fig.2 Number of sensors versus Coverage of a Network

This graph shows that the coverage level of the network is increased with the sensors.



Fig.3 Fusion Rate versus Aggregation Time

The aggregation time for fusing the data is reduced so that the delay is reduced.



Fig 4 Fusion Range of a network versus Signal to Noise ratio

As the Signal to Noise Ratio is increasing the Fusion Range of a network also increases.

4. CONCLUSION

The sensor measurements from different sensors are fused and have to make decision by value fusion method. The dynamic clustering algorithm will be implemented, a cluster formed by the sensors within the fusion range from the possible target to make a detection decision. The optimal fusion range that maximizes the coverage of regular network will increase with network density.

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