4-22-2015

On a Grid-based Solution to Target Detection Through Sensor Deployment and Data Fusion

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ON A GRID-BASED SOLUTION TO TARGET DETECTION THROUGH SENSOR DEPLOYMENT AND DATA FUSION

by

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A Thesis

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

Major: Computer Science

The University of Memphis

May 2015

Acknowledgements

Thanks to all the faculty of Computer Science department. Thanks to Dr. Wang, Dr. Phan and Dr. Fleming for being my committee members. Thanks to my family. Last, but certainly, not the least, many thanks to my advisor Dr. Wu.

Abstract

Yu, Hanwen. M.S. The University of Memphis. April, 2015. ON A GRID-BASED SOLUTION TO TARGET DETECTION THROUGH SENSOR DEPLOYMENT AND DATA FUSION. Major Professor: Chase Qishi Wu

Target detection is one of the fundamental problems in sensor network-based applications. We propose a generic grid-based target detection solution, referred to as GridTD, which integrates data fusion and sensor deployment for the detection of a single static or moving target. GridTD determines a sensor deployment scheme based on cluster analysis, and divides the deployed sensors into several subsets, for each of which, a grid map of the entire region is constructed to estimate the target location using a statistical analysis method under a certain signal attenuation model. A final detection decision is made according to the clustering degree of the estimated target locations from all the sensor subsets. GridTD has potential to achieve a satisfactory performance through a global optimization strategy. Simulation results show the performance superiority of the proposed solution over several well-known methods for target detection.

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Chapter 1

Introduction

Sensor networks have found pervasive applications in many agricultural, civil, industrial, and military domains for various purposes [1, 2, 3, 4, 5]. Target (i.e., signal source) detection is considered as one of the fundamental problems in such sensor network-based applications and has been the focus of research for decades. The majority of the existing research efforts on target detection are focused on one single technique through either data fusion or sensor deployment. Combining such techniques to improve runtime efficiency and detection performance still remains largely unexplored.

Several methods for target detection exemplified by Maximum Likelihood Estimation (MLE) [6] employ a grid-based data fusion approach. In these grid-based detection methods, the key idea is to construct a grid map of the entire region, use the signal probability density function to formulate a statistical framework at each grid point, and make a detection decision at the grid point with the maximum likelihood. These traditional grid-based methods always exhibit a satisfactory detection performance, but are generally computationally very expensive due to the complexity of the likelihood function, especially at high resolutions. More precisely, the detection performance of these methods highly depends on the accuracy of the likelihood function, which in turn determines the complexity of computation. There are cases where the likelihood function may be too complicated to calculate, e.g., in the radiation detection and localization problem with randomness in the source signal and background noise [7, 8]. In such problems, we may only be able to derive an approximate solution.

Sensor deployment is another research direction for target detection (or coverage) in sensor networks. Many conventional sensor deployment strategies consider two objectives: i) the deployment cost, typically determined by the number of sensors to be deployed; and ii) the detection performance such that the entire detection region is covered with the maximum signal strength [9, 10].

We propose a generic grid-based solution for the detection of a single static or moving target, referred to as GridTD, through source localization. GridTD divides the region into grids and determines a sensor deployment scheme based on cluster analysis, where each grid point is treated as a clustering object and each sensor is treated as a cluster center. It then divides the deployed sensors into several subsets, for each of which, a grid map of the entire region is constructed to estimate the target location using a statistical analysis method under a certain signal attenuation model. A final detection decision is made according to the clustering degree of the estimated target locations of all the sensor subsets. Compared with traditional grid-based target detection methods, GridTD avoids complex computation models and improves the detection performance through a global optimization strategy. Simulation results show the performance superiority of the proposed solution over several well-known methods for target detection.

The rest of this thesis is organized as follows. Chapter 2 conducts a survey of related work. Chapter 3 formulates the detection problem. Chapter 4 proposes the GridTD detection method with focuses on data fusion and sensor deployment. Chapter 5 evaluates the performance of GridTD through simulations. Chapter 6 concludes our work.

Chapter 2

Related Work

A detection algorithm infers the presence or absence of a target or a signal source given sensor measurements from a single or multiple sensors. In absence of noise and measurement errors, a detection can be made when the sensor receives a measurement that differs from the background profile. Unfortunately, in practice, sensor measurements are subject to statistical variations of the signal intensity and changes in the background noise.

Many methods and frameworks have been proposed and developed for target detection in different contexts, mainly in two categories: one is localization-based and the other is grid-based [6]. The methods in the first category include i) triangulation-based detection [11], [12], ii) Ratio of Squared Distance (RoSD)-based detection [13], and iii) time difference of arrival (TDoA)-based detection [14, 15, 16]. In general, these localization-based detection methods follow a similar 3-step procedure: a) use a certain attenuation model to build the relation between the source location and the signal strength first; b) construct an equation system to solve for the source location; and c) use the estimated source location to make a detection decision. The main advantage of these methods is that there may exist a fast closed-form solution to the equation system, which makes it very efficient. However, if solving the equation system itself is prohibitively expensive or there are distractive solutions (e.g., "phantom" real roots or even imaginary roots) to the equation system, the robustness of the method would significantly decrease. The detection methods in the second category divide the region into grids, use the signal probability density function to formulate a statistical framework at each grid point, and make a detection decision at the grid point with the maximum likelihood [17, 18, 19]. These methods are able to produce a robust and satisfactory detection performance but at the cost of expensive computation due to the complexity of the likelihood function or the high resolution of the grids.

In addition, a hidden markov random field based detection technique is put forward in [20]. More than that, many other detection methods are based on the statistical techniques, including Bayesian Estimation [21, 22, 23, 24] and Particle Filter [25]. Another representative detection method, i.e., Sequential Probability Ratio Test (SPRT), uses a recursive hypothesis testing method to make a decision through a series of sensor measurements [26, 27, 28].

Considering the pros and cons of the aforementioned traditional detection methods, the goal of this work is to propose a new grid-based method using localization for detection that yields a robust detection performance without involving complex optimization modeling or equation solving.

Chapter 3

Problem Formulation

We consider the deployment of a given set of homogeneous sensors in a two-dimensional (2D) continuous surveillance region R with an arbitrary shape to detect the potential existence of a single static or moving target T.

This problem consists of two major components: sensor deployment that determines where to place sensors in the region and data fusion that determines how to integrate the measurements from individual sensors to make a global detection decision at each time step under two hypotheses: i) H_0: there is no target present, and ii) H_1: there is one target present. Under H_0, we want to minimize the false alarm rate (FR), which is defined as the percentage of time steps that make a false positive decision. Under H_1, we want to minimize the missed detection rate (MR), which is defined as the percentage of time steps that make a false negative decision.

This is a typical passive target detection problem. We consider a generic signal attenuation model defined as a function f of the Euclidean distance d between each sensor and the target or source emitting the signal. The signal strength m emitted by a target T and received by the k-th sensor is calculated as

$$m_k = \frac{A}{f(d_k)} + B_k, \tag{3.1}$$

where A is the original signal strength of the target and B_k denotes the background noise observed by the k-th sensor under a certain probability distribution. Note that different targets such as radioactive, infrared, acoustic, and chemical plume sources feature different forms of attenuation. For example, in radiation detection, $f(\cdot)$ is typically modeled as a quadratic function. However, our proposed method is generic to tackle any form of $f(\cdot)$.

Obviously, on a 2D plane, there are at least two unknowns in Eq. 3.1, i.e., A and d_k (suppose that the background noise could be reasonably estimated from historical data). After replacing d_k and temporarily ignoring the background noise, we can rewrite Eq. 3.1

as

$$m_k = \frac{A}{f(\sqrt{(x_k - x_T)^2 + (y_k - y_T)^2})}, \tag{3.2}$$

where x_k and y_k are the coordinates of the k-th sensor, and x_T and y_T are the coordinates of the source or target T. If a sensor deployment scheme is given, we would know the location of each sensor. Hence, in Eq. 3.2, there are three unknowns, i.e., A, x_T, and y_T.

We formally define a passive target detection problem involving sensor deployment and data fusion, referred to as PTD-SDDF, as follows.

Definition 1 *PTD-SDDF: Given a set of* n *homogeneous sensors* $S = \{s_1, s_2, \ldots, s_n\}$*, a potential target* T *of signal strength* A *with an attenuation model defined by Eq. 3.2, we wish to determine a sensor deployment scheme for the sensor set* S *and a data fusion scheme to integrate the measurement* m_i *from each individual sensor* s_i*,* $i = 1, 2, \ldots, n$*, at a certain time step such that the following detection performance is optimized:*

$$\begin{cases} H_0 : \min(FR), \textit{there is no target present}, \\ H_1 : \min(MR), \textit{there is one target present}. \end{cases} \tag{3.3}$$

The difficulty of PTD-SDDF mainly arises from the fact that both the source measurements under H_1 and the background noise under H_0 contain significant random components in real environments especially outdoors, which rule out any optimal analytical solvers.

Chapter 4

Grid-based Target Detection

We propose a generic grid-based target detection solution, referred to as GridTD, which integrates data fusion and sensor deployment for the detection of a single static or moving target. We first introduce a grid-based data fusion method under a given sensor deployment scheme and further design a systematic approach to sensor deployment.

4.1 Grid-based Data Fusion

In GridTD, the region R is first divided into a number of uniform contiguous grids, each of which is indexed by a pair (i, j). Assuming that the source be located at a certain grid point, for a given sensor deployment scheme, we could estimate the signal strength A from the measurement of each deployed sensor under a given attenuation model according to Eq. 3.2. Obviously, the accuracy of the signal strength estimate depends on the distance between the grid point (an assumed source location) and the true source location: the closer the grid point is to the true source location, the more accurate the source signal strength estimate is. Hence, the grid point that is the closest to the true source location would lead to the most accurate estimate of the actual signal strength. We could measure the similarity in such signal strength estimates by calculating their standard deviation, and use the similarity measurement (i.e., standard deviation) to indicate the existence of a potential target.

However, even if there is no source present, there still exists a grid point with the minimum standard deviation of signal strength estimates. To tackle this issue, we partition the deployed sensors into a number of subsets and use each subset of sensors to find the source location with the minimum standard deviation of the signal strength estimates. If there is a source present, each subset of sensors would lead to a similar source location estimate (around the true source location), as shown in Fig. 4.1(a); otherwise, each subset of sensors would lead to a different source location estimate (around the centroid of the subset), as shown in Fig. 4.1(b). Therefore, we may make a detection decision based on the compactness of the source location estimates calculated from all the subsets. The key

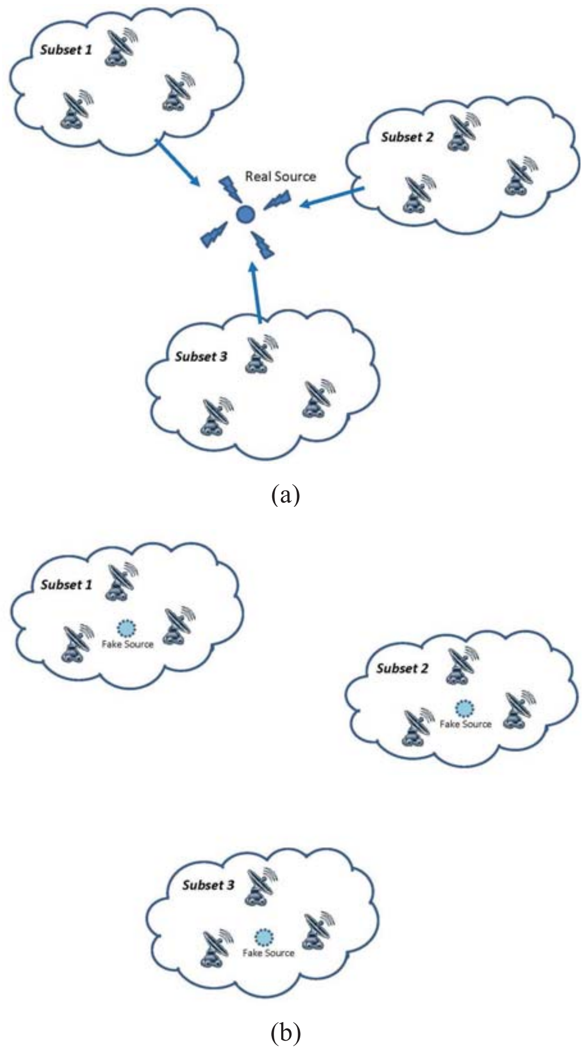

Figure 4.1: (a) The GridTD method with a source. (b) The GridTD method with no source.

steps of the GridTD algorithm are provided in Alg.1.

In Step 1, similar to other grid-based approaches, the number of grids is determined by the requirement on the resolution and the constraint on the computational overhead.

In Step 2, we need to choose an appropriate value for the number w of subsets, which determines the number of sensors in each subset. More sensors in the subset would produce more information about the source signal but meanwhile also increase the overhead of computation. In practice, we choose a value for w such that the average number of sensors in each subset $\frac{n}{w} \geq 10$. When n is small, we may exhaust the combinations of w subsets to form $\sum_{i=1}^{n/w} C^i_{n/w}$ new subsets.

Algorithm 1 GridTD

Input: a set of n sensors s_i deployed at (x_i, y_i) and their respective received signal strength $m_i, i = 1, 2, \ldots, n$.

Output: a detection decision on the existence of a potential source.

1: Divide the region R into $p \times q$ uniform contiguous grids, each of which is indexed by a pair (i, j), $i = 1, 2, \ldots, p, j = 1, 2, \ldots, q$.

2: Partition the given sensors into w non-overlapping subsets using the k-means method.

3: For each subset of sensors, find the grid point (i, j) with the minimum standard deviation of signal strength estimates as the source location estimate.

4: Calculate the clustering degree of all the source location estimates (i, j)'s obtained by Step 3.

5: Compare the clustering degree in Step 4 with a threshold: if the clustering degree is higher than the threshold, there is a source; otherwise, there is no source.

There are different ways to calculate the clustering degree for measuring the compactness of all the source location estimates obtained in Step 4 [29], [30]. In this work, the clustering degree is reflected by the average distance between the source location estimates and their center: a higher clustering degree (i.e., a smaller average distance) means a more dense (or compact) distribution of the source location estimates.

GridTD does not involve any complex optimization model. The time complexity of GridTD is $O(p \cdot q \cdot n + w)$, where w is the number of sensor subsets, excluding the standard k-means method in Step 2. We would like to point out that the algorithm framework of GridTD is suitable for parallelization because the signal strength estimation on each grid point for each sensor is independent of each other.

4.2 Sensor Deployment for Target Detection

The data fusion algorithm discussed above is based on a given sensor deployment scheme, which is another important component of GridTD. We design a cluster analysis-based sensor deployment strategy with the following two requirements under the proposed target detection framework:

1) The sensors should be spread out as far as possible: If the sensors are too close to each other, they would produce similar measurements whether or not there is a source. In

this case, no matter how the sensors are divided into subsets, the estimated source locations with the minimum standard deviations obtained by these subsets would be in a close proximity, leading to a high clustering degree and hence making it hard to distinguish whether or not there is a source.

2) The sensors should cover the region as much as possible: In the presence of a source, we wish to receive a high signal strength at each sensor to resist the background noise. Since the received signal strength depends on the distance between the sensor and the source, each possible source location (i.e., each grid point) should be close enough to one of the sensors to guarantee a high received signal strength.

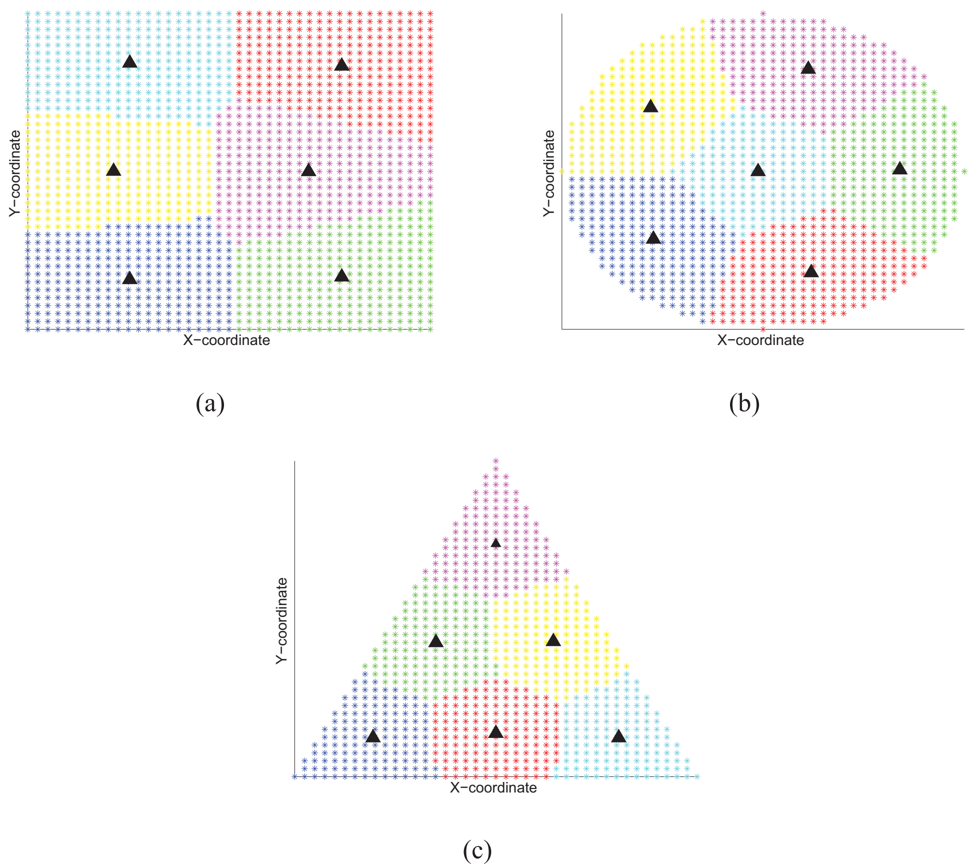

Figure 4.2: Representative sensor deployment schemes with 6 sensors (a) in a square region, (b) in a circular region, and (c) in a triangular region, based on the k-means clustering method.

Therefore, if we treat each gird point as a clustering object and each sensor as a cluster center, we are able to convert the sensor deployment problem into a clustering problem with two similar requirements: 1) the distance between two cluster centers should be as far as possible, and 2) within each cluster, the objects should be as close to the cluster center as possible. There exist many algorithms for this kind of semi-supervised clustering problem, including the k-means method. By applying the k-means clustering model to our sensor deployment problem, we have the following optimization objective:

$$\min \sum_{i=1}^{n} \sum_{(p_j, q_j) \in C_i} e_j \cdot (\|p_j - u_i\|^2 + \|q_j - v_i\|^2), \tag{4.1}$$

where p_j and q_j denote the location of the j-th grid point, u_i and v_i denote the location of the i-th sensor, k is the number of sensors and C_i denotes the i-th cluster. The weight coefficient e_j could be used to assign a priority to a certain area. Intuitively, larger e_j would attract more sensors to be deployed in that area. For example, we may assign a larger e_j to the grid points close to the edges of the region to enhance the boundary detection performance. Fig. 4.2 illustrates three simple and representative deployment schemes with 6 sensors in (a) a square, (b) a circular, and (c) a triangular region, respectively, obtained by the proposed deployment strategy with equal e_j's.

Chapter 5

Performance Evaluation

We conduct a simulation-based performance evaluation and illustration of the proposed GridTD method in comparison with several existing methods for passive target detection widely adopted in real applications. We shall start with a brief introduction to each of these methods.

5.1 Detection Methods in Comparison

5.1.1 Sequential Probability Ratio Test (SPRT)

SPRT is a classical target detection method that makes a detection decision under two hypotheses (a null hypothesis H_0 and an alternate hypothesis H_1) or rejects to make a decision [26]. SPRT accumulates the measurements m from n sensors within a time window of t time steps, denoted by $M = \{m_i^k\}$, $i = 1, 2, \cdots, n$, and $k = 1, 2, \ldots, t$, and defines a lower threshold $TH(H_0)$ and an upper threshold $TH(H_1)$. It then calculates a probability ratio $L = \frac{P(M|H_1)}{P(M|H_0)}$ and compares it with these two thresholds: if L is below $TH(H_0)$ or above $TH(H_1)$, it claims no source present or the presence of a source; otherwise, it rejects to make a decision. It is worth pointing out that in SPRT there are four important parameters one has to set, i.e., the required false alarm rate, the required missed detection rate, and the received signal strength and the background noise for each sensor. In the simulation, we choose appropriate values for these parameters based on the models used to generate the measurement data.

5.1.2 Majority Vote (MV)

MV is a simple hard fusion method, whose basic idea is as follows: each sensor makes a local binary detection decision based on its received signal strength and a predefined threshold, and a global decision is reached based on the rule of "majority wins". In our experiments, the threshold of MV is set to be the mean of the background noise.

5.2 Simulation Settings

In the simulation, we consider a square region of 10×10 meters^2, which is divided into a set of grids with an interval of 0.1 meters along both dimensions. We consider 7 problem sizes based on 15 to 45 homogeneous sensors with an increment of 5 sensors, available for deployment within the region.

We run the detection experiments in two cases: i) Case 1: a single static source with weak or strong signal strength; and ii) Case 2: a single moving source with weak or strong signal strength. In Case 1, the experiment lasts for 2 minutes: in the first 60 seconds, there is no source present, and in the last 60 seconds, there is a static source. In Case 2, the experiment lasts for 40 seconds: in the first 20 seconds, there is no source present, and in the last 20 seconds, there is a moving source. Under each case, we repeat the experiments 10 times with different random seeds and measure the average detection performance.

In the simulation, we generate the source signal strength A and the background noise b_k for sensor s_k, both following the Poisson distribution, and adopt a quadratic signal attenuation model:

$$m_k = \frac{A}{d_k^2} + b_k, \tag{5.1}$$

which represents a typical scenario in radiation detection [18], [21], [22], [23].

In all these experiments, the average strength of the background noise, i.e., the mean value of the Poisson distribution, is set to be 200 counts per second. The weak signal strength is set to be 400 counts per second, and the strong one is set to be 2000 counts per second. Fig. 5.1 exhibits an example. The average strengths of the received signal of all the sensors are shown in Fig. 5.1(a) and Fig. 5.1(b) with a static source, and in Fig. 5.1(c) and Fig. 5.1(d) with a moving source. In Case 1, we randomly place a static source inside an area of 5×5 meters^2 at the center of the region. In Case 2, we simulate a source with either weak or strong signal appearing at the 21st second and moving from position (30, 30) to position (-30, -30) across the region at the speed of $(-0.1, -0.1)m/s$.

5.3 Comparison of Detection Performance

We tabulate the average detection performance in terms of false alarm rate (FR) and missed detection rate (MR) for MV, SPRT and GridTD in Table 5.1. Since MV compares the current measurement with the mean of the background noise, it exhibits a high detection rate

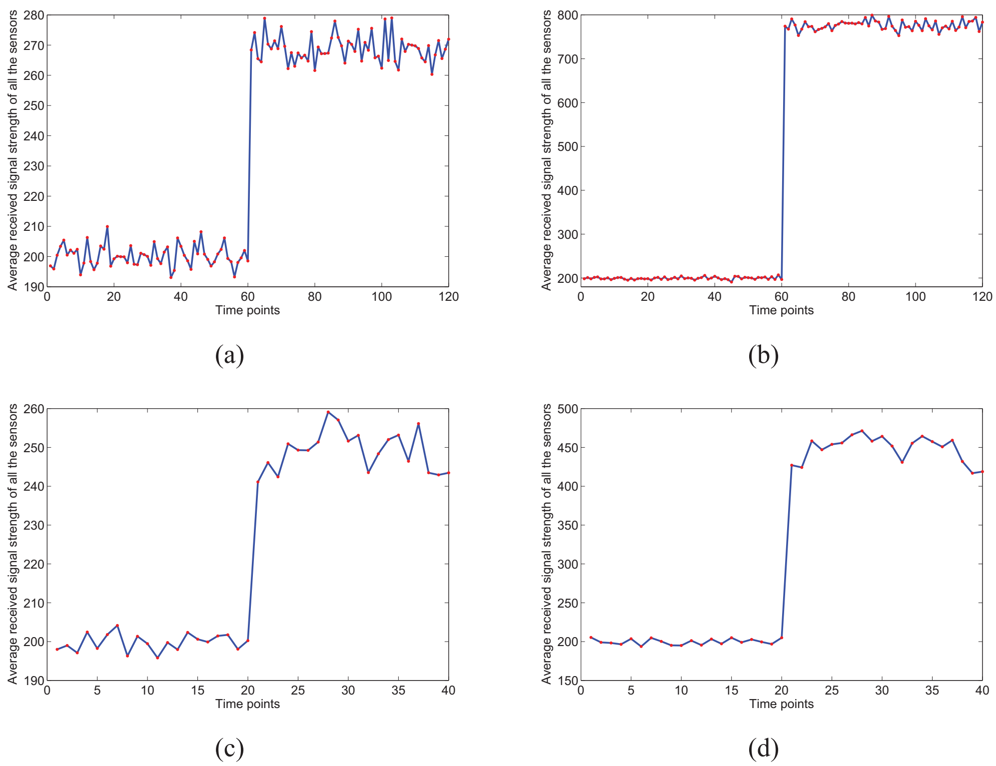

Figure 5.1: (a) The average signal strength of a weak static source. (b) The average signal strength of a strong static source. (c) The average signal strength of a weak moving source. (d) The average signal strength of a strong moving source.

Table 5.1: Comparison of Detection Performance of MV, SPRT, and GridTD.

Prob Size (Number of Sensors)	MV (%)				SPRT (%)			
	Static Source		Moving Source		Static Source		Moving Source	
	FR	MR	FR	MR	FR	MR	FR	MR
15	50.00	0	54.00	0	0	63.00	0	72.00
20	47.67	0	44.00	0	0	56.00	0	79.00
25	45.67	0	59.50	0	0	37.33	0	75.50
30	46.00	0	50.00	0	0	46.33	0	71.50
35	58.67	0	54.00	0	0	48.67	0	74.00
40	48.00	0	51.50	0	0	38.67	0	70.00
45	56.00	0	54.00	0	0	34.33	0	75.00

Prob Size (Number of Sensors)	GridTD (%)			
	Static Source		Moving Source	
	FR	MR	FR	MR
15	3.67	9.00	1.50	38.00
20	8.30	0.67	5.50	20.00
25	8.00	1.30	5.50	22.50
30	5.00	2.30	8.00	18.00
35	0	6.70	8.50	23.00
40	2.50	0	2.50	23.50
45	0.60	1.67	9.50	19.50

(0% missed detection rate) in the presence of a static or moving target. However, this method is very sensitive in the case of no source with a false alarm rate of about 50% and hence presents a serious issue in practical use. Similarly, SPRT uses the parameters for simulation data generation, and performs very well when there is no target present (0% false alarm rate). However, since SPRT attempts to accumulate the measurements over time, there is a delay effect in the detection of a source, hence resulting in a high missed detection rate. Note that it is generally very difficult to choose appropriate values for the parameters in SPRT, which significantly limits its practical use. Compared with these two traditional detection methods, the proposed GridTD method achieves a reasonable detection performance in terms of both FR and MR.

5.4 Illustration of Algorithm Execution

In order to examine the microscopic behaviors of the detection methods in comparison, we provide a detailed illustration of each algorithm execution with 20 sensors.

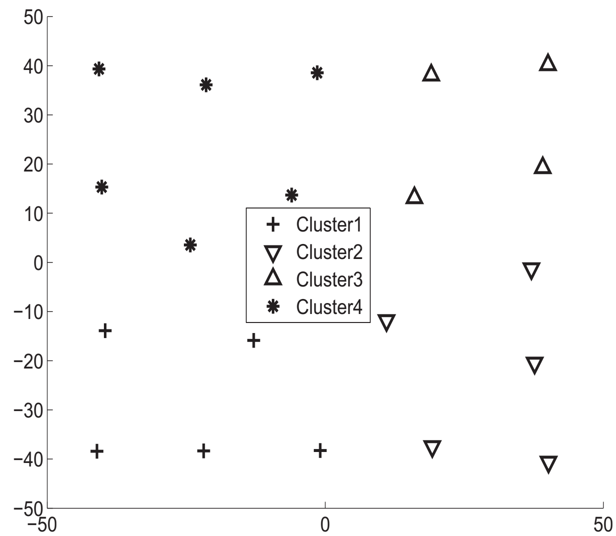

Figure 5.2: The sensor deployment and partition.

5.4.1 Case 1: A Single Static Target with Weak or Strong Signal

We plot the sensor deployment scheme in Fig. 5.2 and partition the sensors into $w = 4$ subsets using the k-means method. Since the number of subsets is limited, we exhaust the combinations of these 4 subsets of sensors to generate more (partially overlapping) subsets to calculate the clustering degree.

The experimental results in the static case are shown in Fig. 5.3. The detection results obtained by the MV method with weak and strong signal are plotted in Fig. 5.3(a) and Fig. 5.3(b), respectively, where the value 1 means that there is a source and the value -1 means that there is no source (the same below). In these two experiments, the threshold of each sensor is set to be the average background noise strength, i.e., 200 counts per second. In Fig. 5.3(a) and Fig. 5.3(b), we observe that the MV method has a false alarm rate of 56.67% and 46.67%, respectively, in the first 60 seconds, and exhibits a good detection performance with 0% missed detection rate in the last 60 seconds.

The detection results obtained by the SPRT method with weak and strong signal strengths are plotted in Fig. 5.3(c) and Fig. 5.3(d), respectively. The SPRT method has the following parameters: a required false alarm rate of 5%; a required missed detection rate of 5%; a background noise strength of 150 counts per second with weak signal and of 250 counts per second with strong signal; a received signal strength of 250 counts per second with weak signal and of 550 counts per second with strong signal. Since it is hard to choose appropriate values for these parameters in SPRT, for an effective comparison, we choose suitable values for these parameters based on the data generation models used in the simulation. In Fig. 5.3(c) and Fig. 5.3(d), we observe that SPRT exhibits a good performance with 0% false alarm rate in the first 60 seconds. Due to the delay effect caused by accumulating the measurements over time, SPRT does not perform well in the first half period of the last 60 seconds, resulting in a missed detection rate of 51.67% and 20%, respectively.

We represent the detection pattern in the proposed GridTD method using the average distance between the source estimates and their center. The detection patterns with weak and strong signal strengths are plotted in Fig. 5.3(e) and Fig. 5.3(f), respectively, in which, the horizontal line with the value of 77 (the same below) represents the threshold of the average distance: if the average distance is higher than the threshold line, claim no source; otherwise, claim a source. In Fig. 5.3(e), we observe that when the signal strength is weak, the GridTD method still exhibits a good performance with a false alarm rate of 5% and a missed detection rate of 3.3%. In Fig. 5.3(f), we observe that with strong signal strength, the detection pattern is much clearer, resulting in a false alarm rate of 6.67% and a missed detection rate of 0%.

The simulation results in Fig. 5.3 show that in the static case, the proposed GridTD method consistently outperforms the MV and SPRT methods in comparison.

5.4.2 Case 2: A Single Moving Target with Weak or Strong Signal

Fig. 5.4. shows the experimental results of the moving case. The detection results obtained by the MV method with weak and strong signal strengths are plotted in Fig. 5.4(a) and Fig. 5.4(b), respectively. In these two experiments, the threshold of each sensor is also set to be the average background noise strength, i.e., 200 counts per second. We observe that the performance of MV in the moving case is similar to that in the static case with a false alarm rate of 45%.

The detection results obtained by the SPRT method with weak and strong signal strengths are plotted in Fig. 5.3(c) and Fig. 5.3(d), respectively. We choose the following values for the four parameters of SPRT: a required false alarm rate of 5%, a required missed detection rate of 5%, a background noise strength of 180 counts per second with weak signal and 200 counts per second with strong signal, and a received signal strength of 400 counts per

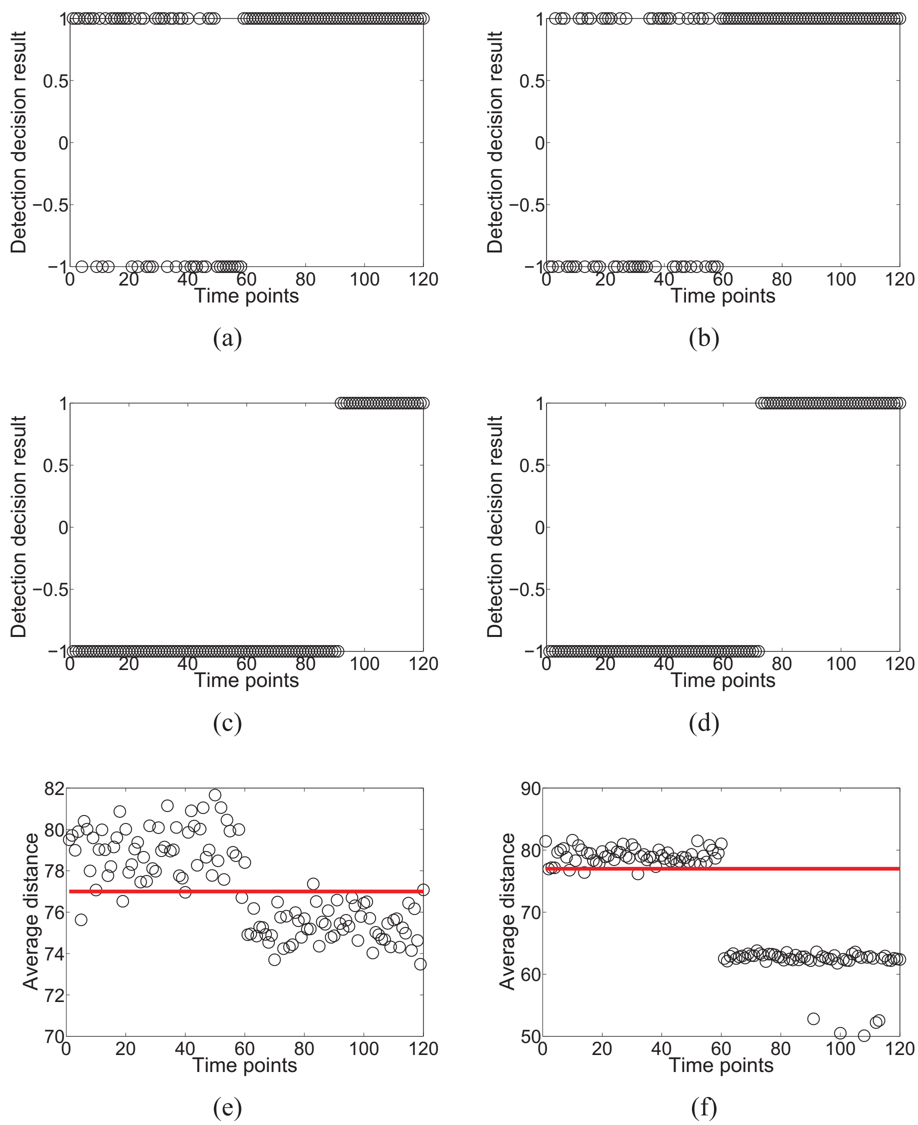

Figure 5.3: The detection results of (a) MV with weak signal strength, (b) MV with strong signal strength, (c) SPRT with weak signal strength, (d) SPRT with strong signal strength, and the detection patterns of (e) GridTD with weak signal strength, and (f) GridTD with strong signal strength, in the static case.

second with weak signal and 2000 counts per second with strong signal. We observe that SPRT achieves a good performance as in the static case when there is no source, but has a missed detection rate of 60% and 50% with weak and strong signal, respectively, in the presence of a source.

The detection patterns (i.e., the average distance between the source estimates and their center) in the proposed GridTD method with weak and strong signal strengths are plotted in

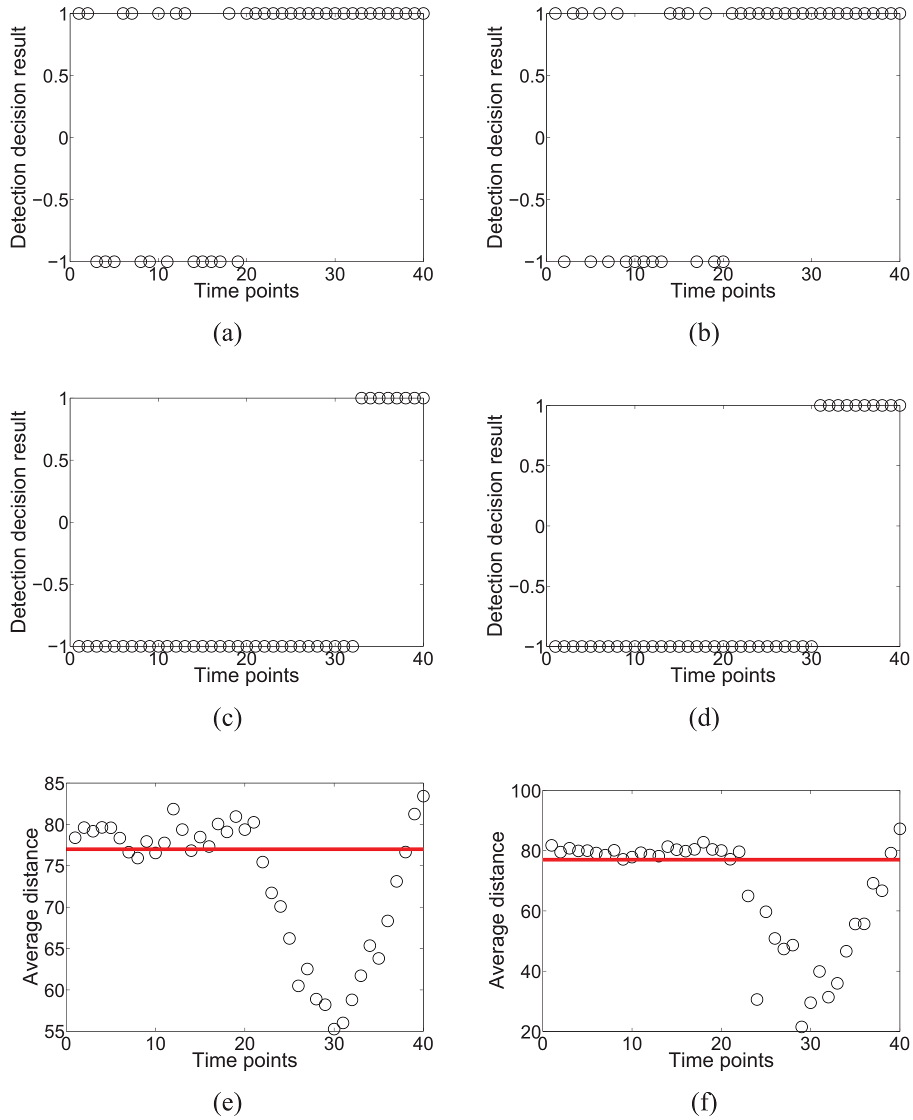

Figure 5.4: The detection results of (a) MV with weak signal strength, (b) MV with strong signal strength, (c) SPRT with weak signal strength, (d) SPRT with strong signal strength, and the detection patterns of (e) GridTD with weak signal strength, and (f) GridTD with strong signal strength, in the moving case.

Fig. 5.4(e) and Fig. 5.4(f), respectively. The threshold of the average distance is again set to be 77 using the same subsets of sensors as in the static case. In Fig. 5.4(e), we observe that GridTD achieves a false alarm rate of 20% and a missed detection rate of 15% with weak signal strength. In Fig. 5.4(f), we observe that the detection pattern is much clearer with strong signal strength, resulting in a false alarm rate of 0% and a missed detection rate of 20%. It is worth pointing out that the detection pattern in the moving case in the presence of a source exhibits a quadratic curve, whose lowest point corresponds to the moment when the source is approaching the center of the detection region such that every sensor is receiving a certain amount of signal. As the source is moving away from the center of the detection region, the amount of signal the sensors receive decreases, hence leading to a larger average distance or a lower degree of clustering among the source location estimates.

The above experimental results show that the proposed GridTD method consistently outperforms the MV and SPRT methods in comparison in the moving case.

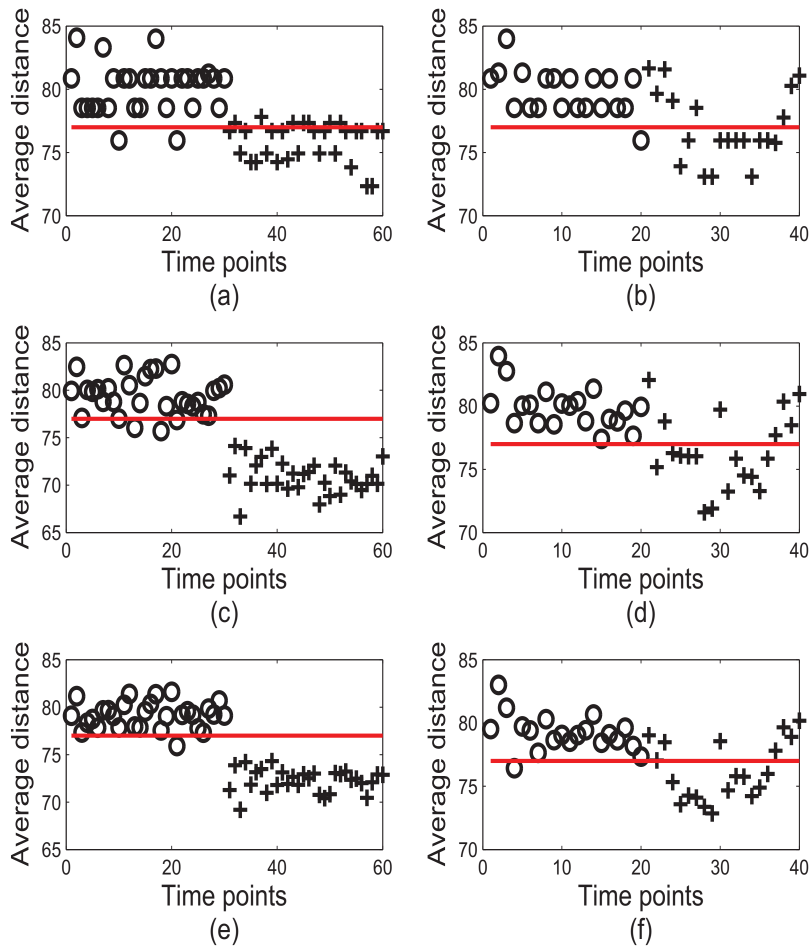

Figure 5.5: The degree of clustering in GridTD under different grid resolutions: the circles represent the situations without a source, and the pluses represent the situations with a static or moving source.

5.5 Illustration of GridTD under Different Resolutions

The performance of GridTD depends on the grid resolution. Fig. 5.5 shows the clustering pattern of the source location estimates for target detection in GridTD under different resolutions. Fig. 5.5(a)(c)(e) plot the degree of clustering in the static case under the resolutions of 1m, 0.5m, and 0.2m, respectively, and Fig. 5.5(b)(d)(f) plot the degree of clustering in the moving case under the resolutions of 1m, 0.5m, and 0.2m, respectively. We observe that the detection pattern becomes clearer as the resolution increases.

Chapter 6

Conclusion

Target detection is one of the fundamental problems in many sensor network-based applications. In this thesis, we proposed a generic grid-based solution that integrates sensor deployment and data fusion for the detection of a single static or moving target. Extensive experimental results show that the proposed solution has a superior performance over several well-known methods for target detection in the static or moving case.

Similar to other threshold-based detection methods, the threshold used in GridTD has a critical impact on the detection performance. Instead of deriving a threshold based on the footprint of the sensor deployment, it is of our interest to develop a systematic approach to decide the threshold. Also, we will compare the time complexity with other grid-based detection methods and determine an appropriate resolution to meet the time requirement of the application.

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