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A Sparse Undersea Sensor Network Decision Support System Based on Spatial and Temporal Random Field

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ABSTRACT

In a sparse sensor network, the sensor detection regions are often not overlapped. The traditional instantaneous detection scheme is less effective due to the fact that targets may not be detected by any sensors at certain sampling instances. To detect the moving targets in a sparse sensor network, we have developed a new system suitable for multiple targets detection and tracking. An optimization based random field estimation method has been developed to characterize spatially distributed sensor reports without making any assumptions of their underlying statistical distributions. FBMM (Forward & Backward Mapping Mitigation) technology is developed to reduce the false detections resulted from the random field estimation. To further reduce the false detections, the refined random field is clustered using gap statistics. STLD (Spatial & Temporal Layering Discrimination) method is developed to individual clusters and true sensor detections are determined based on both spatial and temporal patterns. Simulation results have shown that our system can effectively detect multiple target tracks in a large surveillance region.

Keywords: target detection and tracking, spatial and temporal random field, sparse sensor network, Linear Matrix Inequality, situation awareness

I. Introduction

In a sparse undersea sensor network, the sensor coverage areas are often non-overlapping. This type of surveillance network can achieve a reasonable target detection accuracy while minimizing the overall system cost. Although targets in the surveillance region may not always be detected, as they move, sensors can collectively detect, classify and track them. The traditional instantaneous target detection methods are less effective since, at certain sampling instances, targets may not be detected by any sensors at all. Therefore, operator must evaluate the sensor reports over a period of time. Since it is inevitable for sensors to generate false reports, over the entire evaluation period such as a few hours, both positive and false reports co-exist, making it difficult, if not impossible, for the operator visually or computer autonomously to identify the tracks.

One approach in detecting and tracking undersea targets in a spare sensor network is through characterization of spatial statistical distribution. The probabilistic conceptualization of phenomena in space via the geostatistical approach can be viewed as the study of random phenomena in time (Bancroft and Hobbs, 1993). Sequences of observations in time or space may both be viewed as single realizations of jointly distributed random variables. A collection of random variables in time defines a stochastic process. In geostatistics the collection of random variables is defined on points in space. In the geostatistical literature, the probability law governing this collection of random variables defined on points in space is commonly referred to as a point random function following the terminology of Yaglom (1962). Any variable which value is related in some way to its position in two- or three-dimensional space is called a regionalized variable after Matherton (1971).

The essential problem in geostatistics is to estimate the directional parameters. There are at least two different approaches used to solve this problem: random field (RF) modeling (Gaussian, Markov, or Gaussian-Markov), and kirging (simple kriging, universal kriging, etc.). In random field modeling setting, it is always assumed that spatial data are stationary and Gaussian distributed with known or empirical mean and variance. Gaussian Random Field (GRF) or Gaussian-Markov Random Field (GMRF) modeling has been widely used in image processing (Deng, 2004). In undersea sensor network, the assumption of stationary process and Gaussian or Markov distribution need to be carefully verified.

On the other hand, the kriging technique estimates the directional parameters by error variance minimization (Chiles, 1999). However, there are three underlying assumptions of kriging: (1) The spatial variability of the samples can be adequately represented by a semi-variogram; (2) The sample values approximate a statistical normal (Gaussian) distribution; and (3) There is no spatially determinate trend present in the samples. Although these assumptions ensure an optimal kriging with minimum uncertainty and maximum confidence, they are often not satisfied in the applications of undersea target detection and tracking.

To detect the moving targets in a sparse sensor network, we have developed a new system suitable for multiple targets detection and tracking. An optimization based random field estimation method has been developed to characterize the spatially distributed sensor reports without making any assumptions of their underlying statistical distributions. FBMM (Forward & Backward Mapping Mitigation) technology is applied to reduce the false detections resulted from the random field estimation. To further reduce the false detections, a refined random field is clustered using gap statistics. STLD (Spatial & Temporal Layering Discrimination) method is applied to the individual clusters and true sensor detections are determined based on both spatial and temporal patterns. Simulation results have shown that our system can effectively detect and track multiple targets in a large surveillance region.

This paper is organized as follows: The general random field for undersea sensor network is described in Section 2. Our new non-parametric random field estimation method is given in Section 3. Then in Section 4, forward & backward mapping mitigation method for false reports reduction is described. And finally, the spatial & temporal layering discrimination and related simulator are given in Section 5.

II. General Random Field for Undersea Sensor Network

Let $\{Z(\boldsymbol{s}, t) \mid \boldsymbol{s} \in D \subset R^d; t \in [0, \infty)\}$ denote a spatial-temporal random process observed at n space-time coordinates $(\boldsymbol{s}_1, t_1), \ldots, (\boldsymbol{s}_n, t_n)$. One example of Z can be the p-value associated with the detection confidence of each sensor. Optimal prediction in space and time based on the observations

$$\boldsymbol{Z} = [Z(\boldsymbol{s}_1, t_1), \ldots, Z(\boldsymbol{s}_n, t_n)] \tag{2-1}$$

is required to infer the value of some unobserved spatial-temporal points. It is often assumed $Z(\boldsymbol{s}_1, t_1), \ldots, Z(\boldsymbol{s}_n, t_n)$ are a realization from some underlying random fields such as spatial and temporal fields. Let $Z(\boldsymbol{s}_0, t_0)$ be a spatial-temporal point. The objective is to find its optimal estimate based on observations given in (2-1).

If we only consider the spatial random field, the observations in (2-1) can be simply expressed as

$$\boldsymbol{Z} = [Z(\boldsymbol{s}_1), \ldots, Z(\boldsymbol{s}_n)] \tag{2-2}$$

If $\{Z(s_i), i = 1, \ldots, n\}$ are the realization of a Gaussian process, kriging linear estimator yields an optimal prediction:

$$Z^*(\mathbf{s}_0) = m + \sum_{i=1}^{n} w_i\big(Z(x_i) - m\big) \tag{2-3}$$

where m is the mean of the process, the weights, $w_1, \ldots, w_n$, can be estimated by minimizing the covariance function, which is also known as simple kriging. Details of kriging can be found in most text books (for example, Chiles 1999).

There are three underlying assumptions of kriging:

(1) The spatial variability of the samples can be adequately represented by a semi-variogram;
(2) The sample values approximate a statistical normal (Gaussian) distribution;
(3) There is no spatially determinate trend present in the samples.

These assumptions ensure an optimal kriging with minimum uncertainty and maximum confidence. The first assumption implies that $\{Z(\boldsymbol{s}_i, t_i)\}$ are second-order stationary:

$$E(Z(\boldsymbol{s}_{i+h}, t_{i+h})) = E(Z(\boldsymbol{s}_i, t_i)) \tag{2-4}$$
$$\mathrm{cov}(Z(\boldsymbol{s}_{i+h}, t_{i+h}), Z(\boldsymbol{s}_i, t_i)) = \mathrm{C}(h) \tag{2-5}$$

As reported in (Cressie, 1986), this assumption is often violated in real applications. Therefore, we must consider kriging with non-stationary data. The second assumption must also be verified in the undersea sensor network applications. There is no general treatment for non-Gaussian data.

The third assumption will certainly not be satisfied in the undersea sensor network environment. When the target(s) are in the surveillance region, a spatial-temporal trend is inevitable, which is resulted from the movement of the target(s). This violation implies that the traditional kriging is not applicable for the undersea target detection application. One possible solution is to apply Bayesian analysis to construct an optimal estimator (Handcock 1993).

A good starting point for the target detection and tracking in the undersea sensor network is to construct the probabilistic random field model. In addition to the spatial covariance among sensors, temporal variation of individual sensors should also be considered. In this way, both time-invariant and time-dependent random fields can be spatially interpolated, thus, improving the prediction of unobserved spatial-temporal points in the detection region. By incorporating the temporal variation at individual sensors, we can effectively capture the variation of sensor detections.

III. Non-Parametric Estimation of Random Field – A New Approach

We consider an $N \times M$ random field $Z = \{z_{ij}\}$ defined over a finite 2-D lattice $\Omega = \{(i, j) \mid 0 \le i \le N, 0 \le j \le M\}$. The values of z_{ij} are a realization of random variable $Z = \{Z_{ij} \mid (i, j) \in \Omega\}$. The random field model we consider here can be described by the following difference equation:

$$z_{ij} = \sum_{(i+r,\, j+s) \in N_{ij} \subseteq \Omega} \beta_{rs} z_{i+r,\, j+s} + \upsilon_{ij} \tag{3-1}$$

where N_{ij} is a neighborhood centered at (i, j), and $\{\upsilon_{ij}\}$ is a Wiener random process. β_{rs} is the parameter describing the directional information between location (i, j) and (i+r, j+s). Our goal is to estimate z_{ij} based on the measurements such as p-values of the sensor detections.

Let $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_D]^T$ be the real weight vector. For simplicity, denote z_{ij} as z_f. Then the random field z_f can be expressed as

$$z_f = \sum_{i=1}^{D} \beta_i z_i = \boldsymbol{\beta}^T \mathbf{Z} + \nu \tag{3-2}$$

where D is the number of sensor nodes considered. Here we treat β_i as a general weighting factor placed on the ith sensor. We don't make any assumptions about any prior knowledge of the system operation environment. *Based on the continuation of sensor outputs, the random field z_f over two consecutive samples must be similar provided that the sampling rate is large enough or the sampling time is small enough*. Mathematically, suppose z_f^k and z_f^{k+1} are the random fields at the sampling time instants k and k+1. Then, based on the continuation property, the quantity of $\| z_f^k - z_f^{k+1} \|$ is small, which is the cornerstone of our non-parametric random field estimation method.

Our optimization scheme is formulated as

$$\begin{aligned} &\textit{Minimize}: && \varepsilon \\ &\textit{Subject to}: && \| z_f^{k+1} - z_f^k \|_2^2 < \varepsilon \end{aligned} \tag{3-3}$$

where $z_f^k = \boldsymbol{\beta}^T \mathbf{Z}^k$, and $z_f^{k+1} = \boldsymbol{\beta}^T \mathbf{Z}^{k+1}$, and $\mathbf{Z}^k$ and $\mathbf{Z}^{k+1}$ are the sensor output matrices given in (3-2) at the sampling time instants k and k+1. It follows that

$$\| z_f^{k+1} - z_f^k \|_2^2 = \left(\Delta \mathbf{Z}_k^{k+1}\right)^T \mathbf{B} \left(\Delta \mathbf{Z}_k^{k+1}\right) \tag{3-4}$$

where $\Delta \mathbf{Z}_k^{k+1} = \mathbf{Z}^{k+1} - \mathbf{Z}^k$ and $\mathbf{B} = \boldsymbol{\beta}^T \boldsymbol{\beta}$. It is clear that $\mathbf{B} > 0$ because $\beta_i > 0$ for $i = 1, 2, \ldots, D$. Therefore,

$$\| z_f^{k+1} - z_f^k \|_2^2 < \varepsilon \tag{3-5}$$

is equivalent to

$$\varepsilon \mathbf{I} - \left(\Delta \mathbf{Z}_k^{k+1}\right)^T \mathbf{B} \left(\Delta \mathbf{Z}_k^{k+1}\right) > 0 \tag{3-6}$$

Using Schur compliments (Boyd, 1994), (3-6) is equivalent to the following linear matrix inequality:

$$\begin{bmatrix} \varepsilon \mathbf{I} & \left(\Delta \mathbf{Z}_k^{k+1}\right)^T \\ \Delta \mathbf{Z}_k^{k+1} & \mathbf{B} \end{bmatrix} > 0 \tag{3-7}$$

Consequently, the nonlinear optimization problem defined in (3-3) can be written as:

$$\begin{aligned} &\textit{Minimize:} \quad \varepsilon \\ &\textit{Subject to:} \quad \begin{bmatrix} \varepsilon\mathbf{I} & \left(\Delta\mathbf{Z}_k^{k+1}\right)^T \\ \Delta\mathbf{Z}_k^{k+1} & \mathbf{B} \end{bmatrix} > 0, \quad \mathbf{B} > 0 \end{aligned} \tag{3-8}$$

which is a standard LMI (Linear Matrix Inequality) problem (Boyd, 1994).

Our LMI-based random field estimation method defined in (3-8) solves for the weight vector $\beta = [\beta_1, \beta_2, \ldots, \beta_D]^T$ used in the estimation of random field expressed in (3-2). Compared to the existing GRF, GMRF models, or kirging method, our approach does not depend on the prior statistical knowledge of sensor measurement.

We have performed a series of tests and compared our testing results with kriging in the software program, EasyKrig (version 3.0). Figure 3-1 shows one example of a surveillance region with one target. For this simulation example, we assume that there are multiple sensors (labeled as diamond) that have detected the target.

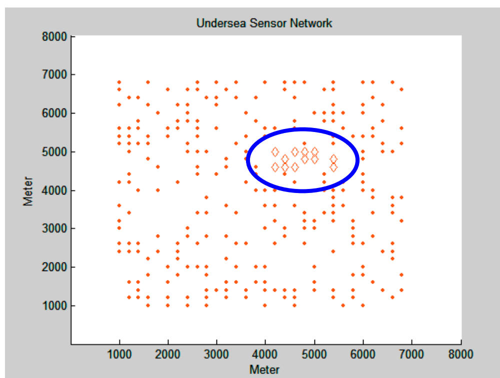
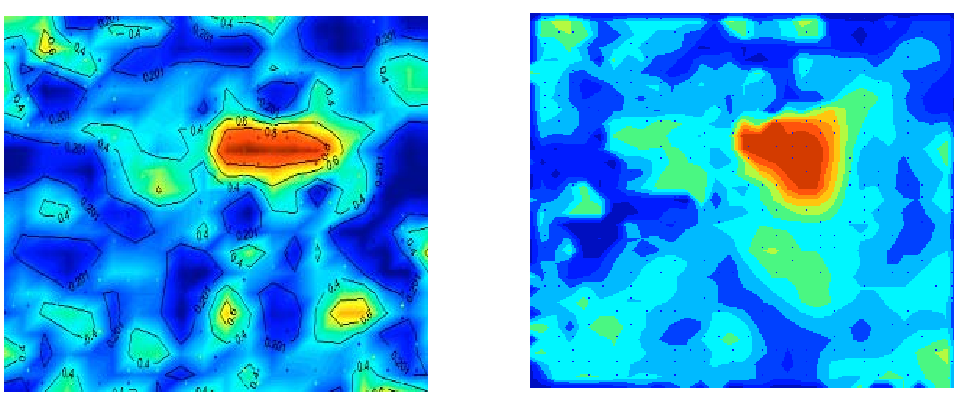


Figure 3-1: An example of a sensor network with one target present.

Figure 3-2 shows the estimated random field using our LMI-based method (right) and kriging method (left). It can be observed that our LMI-based random field is smoother than kriging-based random field. The region with positive detection is larger than what given by kriging random field.



(a) Kriging method

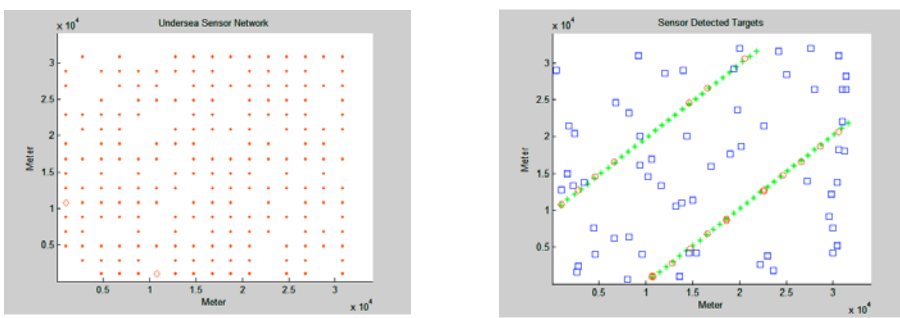
(b) Our LMI method

Figure 3-2: Estimated random field based on LMI (right) and kriging (left).

IV. Forward & Backward Mapping Mitigation

Our detection strategy is to sample the sensors over a period of time and analyze the trajectories formed by the geo-locations of sensors which have detected the targets. Although one particular sensor may or may not detect a target at a particular sampling time instance, a number of sensors sampled over a period of time can collectively detect the moving targets. However, this approach for the target detection at sensor network level is effective only if there are *no* false reports. Although the false report rate is expected to be low, over the period of observation time such as a few hours, the number of sensors generating false reports can be large enough to make it difficult to detect the targets based on their trajectory analysis.

For example, suppose there are total 200 sensors deployed in a surveillance region of 20×20 sq. miles. We sample the sensors every four minutes over a period of two hours, resulting total 30 sampling instances. We further assume that there are only 1% of deployed sensors which will generate false reports. In this case, at each sampling time, there will be two sensors generating false reports. Over 120 minutes period, there will be 60 sensors generating false reports. The number of sensors generating true reports is random since sensors are randomly deployed and subject to drifting. Figure 4-1 shows the sparse sensor network and the sensor reports generated over a period of two hours. There are two targets moving at the speed of 180 meter/hour. The sensors with the positive detection are shown in red circle, and those having the false reports are labeled with blue squares.



(a) Sparse sensor network (b) Sensor reports with groundtruth

Figure 4-1: Sparse sensor network and sensor reports generated over a period of two hours.

Figure 4-2 shows what an operator will typically see at the end of two-hour evaluation period. Without the groundtruth, it is difficult to determine whether or not there are targets and where the target tracks are. In this example, there are 60 false reports and 20 positive reports. Both positive and false reports are mixed together.

Figure 4-2: Sensor reports (true and false) over a period of two hours.

If we search for target tracks in Figure 4-2, there will be potentially many track candidates and most of them are false. Therefore, we need to reduce as many false tracks as possible. In our system, we apply our patented technology called Forward & Backward Mapping Mitigation (FBMM). As illustrated in Figure 4-3, FBMM is primarily made of three modules – Forward Mapping, Mitigation, and Background Mapping.

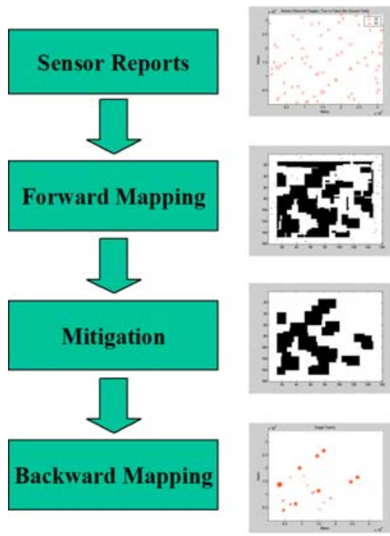


Figure 4-3: Three primary modules associated with FBMM.

In the following, we briefly describe individual modules and their implementation:

(1) Forward Mapping

In this module, the sensor reports over the period of observation time is processed for the estimation of random field. The goal is to explore the spatial correlation among the sensors with either true or false reports. At this stage, all sensor reports are treated equally since there is no prior knowledge about the true detection status of individual sensors. In our system, we have applied our LMI-based method for the random field estimation.

(2) Mitigation

The random field resulted from the forward mapping method explores all potential spatial correlation among the sensors that have generated detection reports (true or false). Therefore, this random field contains false neighborhood detections which must be eliminated. One way to reduce the false detections is to compare the structures embedded in the random field. In our system, we convert the random field into an image setting and apply the mathematical morphological closing operator to reduce the false reports.

(3) Backward Mapping

To further eliminate the false reports resulted from the random field estimation, we map the mitigated random field back to the original sensor reports. Isolated false reports are further eliminated, resulting a refined random field (called FBMM random field) with far less number of false reports. It is expected that this process may remove the true reports as well due to the fact that targets are not detected continuously in the sparse sensor network.

Figure 4-4 shows one example of target tracks after applying our FBMM technology. In this figure, the original sensor reports (left) have the true and false reports mixed, making it extremely difficult to determine, even visually, whether or not targets are present. The right figure shows the FBMM random field where target tracks are relatively easy to identify. In the right figure, the sensor nodes are coded both in color and size, indicating the temporal information – darker red and large size nodes indicate the recent detections, while lighter red and small size nodes represent the detection occurred relatively close to the beginning of the observation period.

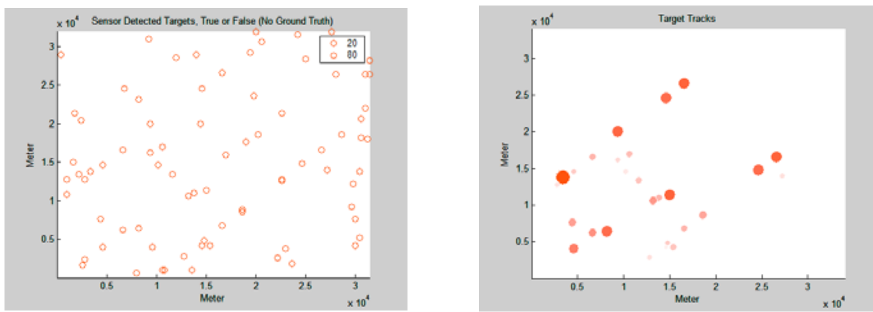


Figure 4-4: Original sensor reports (left) and FBMM random field (right).

From Figure 4-5, it is clear that FBMM method can effectively reduce the false reports and retain the true detections, thus, identifying the target tracks. Figure 4-5 shows another example where no targets are present. The left figure shows the original sensor reports. Although there are no targets present, it is still possible to falsely identify potential target tracks. However the FBMM random field (right figure) clearly indicates that there is no target at all.

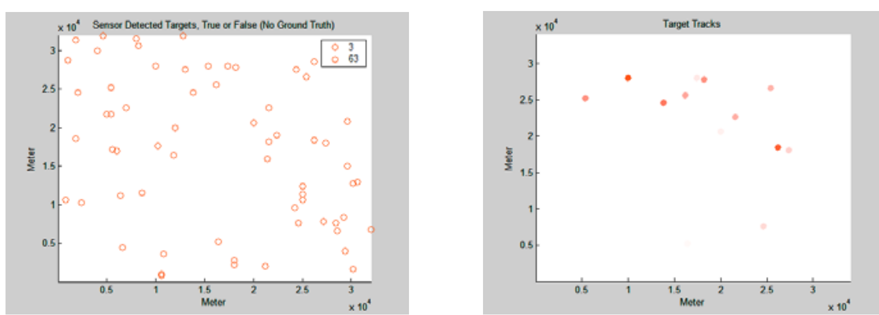


Figure 4-5: Original sensor reports (left) and mitigated random field (right).

V. Spatial & Temporal Layering Discrimination

Although our FBMM method can effectively reduce false detections, as observed in Figure 4-4, there are still false reports left from the random field estimation. To identify the target tracks, we apply our patented technology, Spatial & Temporal Layering Discrimination (STLD), to further reduce the false detections.

Based on the FBMM random field, we choose to apply the clustering method to estimate the potential target tracks. The existing clustering methods such as k-means often require the prior knowledge of the number of clusters. However, since the spatial false detections occur randomly, the number of potential target tracks are unknown.

Our approach is to apply the gap statistics to estimate the number of target tracks and estimate the disconnected track segments. The advantage of this approach is that it is relatively easy to estimate the tracks from the detections in a cluster. The tracks estimated from the clusters become the disconnected or broken track segments. We can then combine these segments to form a refined track.

Gap Statistic (Tibshirani, 2001) is a technique used to estimate the number of clusters in the data. Let data $\{x_{ij}\}$, $i = 1, 2, ..., n$, $j = 1, 2, ..., p$, consist of p features measured on n independent observations. Let $d_{ii'}$ denote the distance between observations i and i'. The most common choice for $d_{ii'}$ is the squared Euclidean distance $\sum_j (x_{ij} - x_{i'j'})^2$. Suppose that we have clustered the data into k clusters $C_1, C_2, ..., C_k$, with C_r denoting the indices of observations in cluster r, and $n_r = |C_r|$. Let

$$D_r = \sum_{i,i' \in C_r} d_{ii'} \tag{5-1}$$

be the sum of the pairwise distances for all points in cluster r, and set

$$W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r \tag{5-2}$$

So, if the distance d is the squared Euclidean distance, then W_k is the pooled within-cluster sum of squares around the cluster means. The Gap statistic is defined as

$$Gap_n(k) = E_n^*\{\log(W_k)\} - \log(W_k) \tag{5-3}$$

where E_n^* denotes expectation under a sample of size n from the reference distribution. The estimated k will be the value maximizing $Gap_n(k)$ after taking the sampling distribution into account.

Figure 5-1 shows six clusters estimated from FBMM random field in Figure 4-4. In each cluster, there are less number of sensor reports distributed both spatially and temporally.

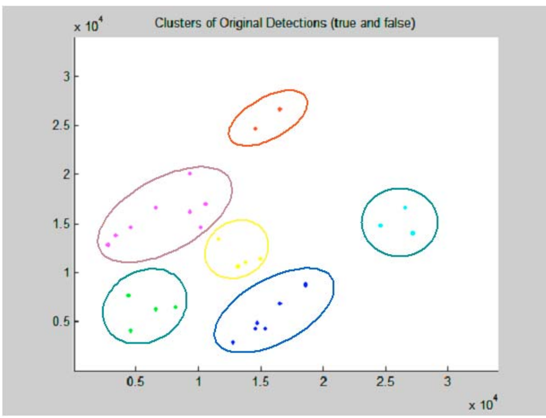


Figure 5-1: Disconnected target tracks based on gap statistics.

The final detections in each cluster are determined from both temporal and spatial patterns. In particular, we check the following two constraints:

(1) Temporal Pattern – True detections must show temporal trend
(2) Spatial Pattern – True detections must be relatively close spatially

The first constraint reflects the fact that, as a target moves, its detections show a temporal trend. Since the target cannot move abruptly, this temporal trend must follow certain kinematic trajectory. The second constraint also has its physical meaning – target trajectory is relatively regular within a small period of time limited by the cluster.

Figure 5-2 shows the STLD random field from which the target tracks can be easily identified. The remaining issue is to estimate the number of targets and their tracks. Since we mainly focus on the operator decision support system, we provide tools for the operator to manually estimate the synthetic tracks.

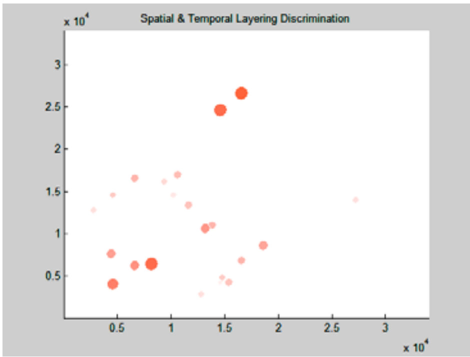


Figure 5-2: An example of STLD random field.

In our system, operator can visually determine the number of tracks and manually locate two points for one track, one for the starting position, the other for the ending position. Based on these two points, a synthetic tracks will be estimated, indicating where the target is heading to. Figure 5-2 shows two tracks (right figure) estimated from the STLD random field given in Figure 5-1 and the groundtruth (left figure).

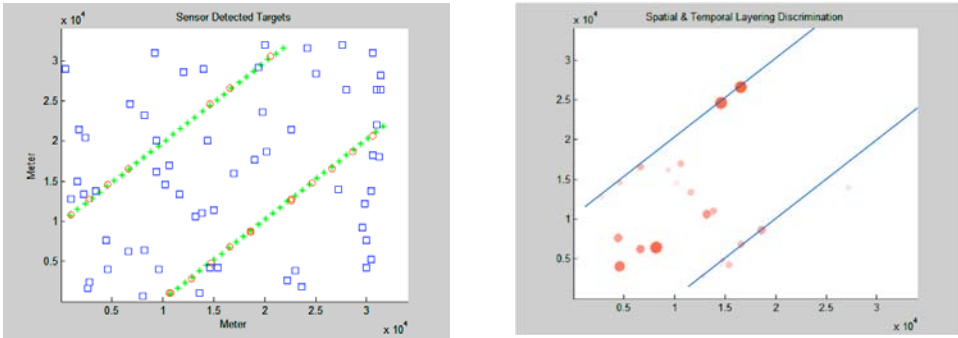


Figure 5-3: Synthetic target tracks (right) and groundtruth (left).

In our future system, operator will be able to identify a number of points on STLD random field and the system will estimate the best kinematic trajectory representing the target movement.

We have also developed a simulator shown in Figure 5-4. At this stage, this preliminary simulator is implemented in Matlab.

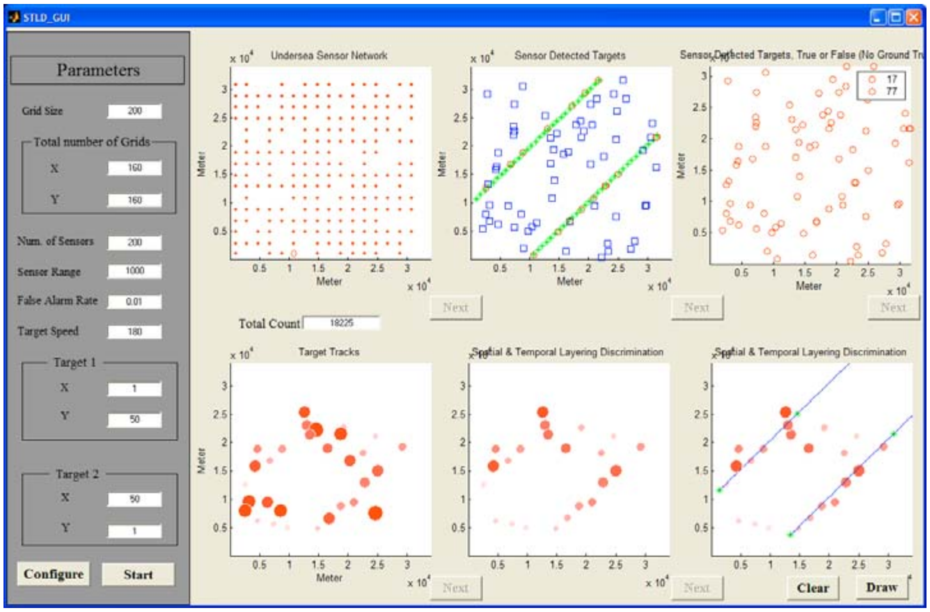


Figure 5-4: A simulator for undersea target detection and tracking in a sparse sensor network.

In this simulator, a user can specify a number of design parameters including:

- network grid size
- total number of grids (equivalent to the area of surveillance region)
- number of sensors randomly deployed in the region
- sensor detection region
- sensor false detection rate
- target speed
- target initial location

An interesting design parameter is the number of sensors to be deployed in a surveillance region. With this simulator, user can specify different number of sensors and determine whether or not the targets can actually be detected. Therefore, use can use this system to estimate the minimum number of sensors necessary for one particular surveillance region.

CONCLUSION

In this paper, we have presented a new system suitable for multiple targets detection and tracking. An optimization based random field estimation method has been developed to characterize spatially distributed sensor reports without making any assumptions of their underlying statistical distributions. FBMM (Forward & Backward Mapping Mitigation) technology is applied to reduce the false detection resulted from the random field estimation. To further reduce the false detections, the refined random field is clustered using gap statistics. STLD (Spatial & Temporal Layering Discrimination) method is applied to individual clusters and true sensor detections are determined based on both spatial and temporal patterns. Simulation results have shown that our system can effectively detect multiple target tracks in a large surveillance region. A preliminary simulator has also been developed. A user can specify a number of design parameters including the number of sensors randomly deployed in a surveillance region.

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