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# Variable and Multiple Target Tracking by Particle Filtering and Maximum Likelihood Monte Carlo Method

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**Abstract**

In most applications for detecting unknown and varying number of target problems based on Joint Probabilistic Data Association, it is difficult to avoid dimensionality curse, which makes the applications very impractical. In this paper, an Algorithm for Detection of Multi-targets in Wireless Acoustic Sensor Networks (ADMAN) and localization algorithm based on Maximum Likelihood Monte Carlo (MLMC) method are introduced. The advantage of ADMAN is its ability to detect any number of targets simultaneously. Once it detects targets, we know the approximate locations of the targets depending on the resolution of the sensor. The locations of targets are estimated by the MLMC method. Since MLMC method is not sequentially performed it is robust after even an error detection is executed. The algorithm can be applied very practically.

## I. Introduction

We use measurement, information to estimate the state of a target of which process is called tracking. Many kinds of physical quantities related with state of the target can be used for the measurement in localization problem such as estimate of position, range and/or bearing , time of arrival difference, frequency of narrow band signal emitted by target, frequency difference due to Doppler shift sensed by two sensors and signal strength which is employed as the measurement of this paper. Among them *Received Signal Strength* (RSS) can be classified in the lowest level and does not need any signal processing to be measurement. In RSS model [1], the measured power is expressed as follows,

$$y_{n,t} = 10\log_{10}\left(\sum_{k=1}^{K} \frac{\Psi_k d_0^{\alpha}}{|\mathbf{r}_n - \mathbf{l}_{k,t}|^{\alpha}}\right) + v_{n,t}, \quad n = 1, 2, \ldots, N \tag{1}$$

where $\mathbf{l}$ is the location of a source target, $n$ is sensor index, $t$ is time instant, $K$ is the number of targets, $\Psi_k$ is the received power from the source at the reference distance $d_0$ (which are assumed known), $\mathbf{r}$ is the location of sensor, $\alpha$ is the attenuation factor ($\alpha \geq 1$), $v$ is background zero-mean Gaussian noise and $N$ is the total number of sensors used in the field.

If the number of targets are time variant the problem will be very challenging due to the dimensionality curse of heavy complexity. Many approaches such as Joint Probabilistic Data Association (JPDA) [2], Multiple Hypothesis Tracking (MHT) [3], Finite Set Statistics (FISST) [4] and Probability Hypothesis Density (PHD) [5] detect and track targets jointly. The size of the state space for the joint distribution over target states is quite huge. All approaches are associated with data association applications based on so called, ‘Bar-Shalom test’ [2] framed by Bayesian filtering.

In this paper, an Algorithm for Detection of Multi-targets in Wireless Acoustic Sensor Networks (ADMAN) with an localization method is introduced. Once the detection algorithm is accomplished we adopt *Maximum Likelihood Monte Carlo* (MLMC) method to estimate the locations of detected targets. We generate particles uniformly in the region that is decided according to the hypothesis decision testing in ADMAN. MLMC method is more robust than sequential method in the sense that any error detection does not affect the future. Also MLMC always stays away from the dimensional curse whereas the sequential Monte Carlo method does not. The advantage of the ADMAN is that it can cope with any varying pattern of the number of targets. In the most applications for multi-target tracking problems based on Joint Probabilistic Data Association (JPDA), it is difficult to avoid dimensionality curse, which makes the applications very impractical. Consequently, changing pattern of the number of targets in the examples of their solutions are very limited and restricted so that it is more or less predictable for detecting changing number of targets [6], [7]. ADMAN shows superiority when the number of targets vary dramatically.

The rest of paper is composed as follows. The ADMAN is introduced for detection of targets in section II. In section III, *Generalized Likelihood Ratio Test* (GLRT) is employed for specific *composite hypothesis testing* problem in ADMAN. *MLMC* method is combined with ADMAN to complete the tracking procedure of the varying multiple number of targets in section IV. In section V, an simulation is presented to show the example of the algorithm. We make conclusions and provide important necessary extension of the work in section VI.

## II. Detection Algorithm

We consider multiple target detection problem as *Composite Hypothesis Testing* [8], where the PDFs under hypotheses are not completely known. The *composite hypothesis testing* problem is solved using *Generalized Likelihood Ratio Test* (GLRT) in this paper. There are a number of solutions to the *composite hypothesis testing* problem, e.g., Bayesian approach, Wald test, Rao test, locally most powerful test, and so on. GLRT is the most pertinent approach among those solutions because we have to estimate parameters in both hypotheses in the ADMAN whereas all other approaches require one known parameter estimate in one hypothesis. ADMAN is explained in this section. We begin with the definition of a couple of important terms that form the bases of the algorithm.

### A. Range ($\mathbf{r_0}$)

Sensors are deployed uniformly and cover the whole area of interest according to a specific range of the sensors except for the in-between part of sensor's range as in figure 1. The *range* ($r_0$) of a sensor is defined as the boundary of region such that the power received by the sensor from any target within the region is greater than a predefined threshold. We can regard the range of the sensor as the capability to resolve two targets because ADMAN does not work if there are more than one target exit within the boundary of the range of a sensor. According to the resolution we assume that more than one target can not exist in a single sensor area (within the circle with the radius of $r_0$). Generally, using ADMAN, detecting more number of targets does not make the problem proportionally more difficult, but the resolution decreases if all other conditions remain the same. The key of ADMAN is attachment of each target to the most pertinent single sensor without redundancy.

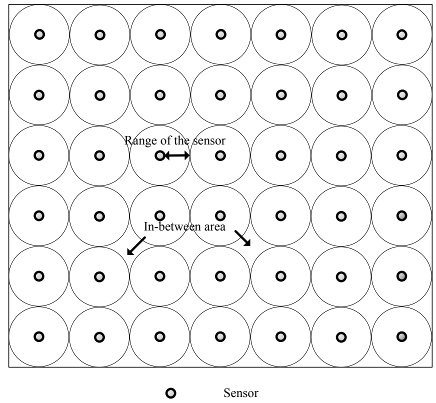


Fig. 1. Uniformly deployed sensors in the field of interest.

When it is assumed that there is always only one target or none in the field of interest, it is easy to attach a target to a sensor which is the closest to the target. Regardless of the size of the range, the threshold is set to be the received power from a target at a distance $r_0$ from the sensor. So the sensor which has the received power signal greater than threshold will be attached to the target at any time instant. An example of attaching in a single target problem is displayed in figure 2. At each time instant, the target is detected and attached to the closest sensor which received the highest power. However, a complicated

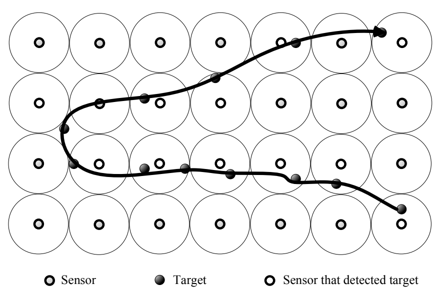


Fig. 2. Attaching a single target. Along with the target track, attached sensor is distinguished by brighter color.

situation will arise when trying to track more than one target at the same time.

Suppose that the maximum number of targets we want to track at the same time is 3, and we may want the range of the sensor to be $r_1$. If we consider the extreme situation that a sensor receives possible strongest power with no detection, in this situation all three targets are located at the distance of $r_1$ from the sensor as (a) in figure 3. Intuitively, we could take this received power as the threshold, and if a sensor receives power greater than this threshold, it decides that there is a single target inside the range of the sensor. However, we can find out obvious errors which are shown in figure 3 if we do not modify the range. With the range $r_1$ and threshold chosen previously, as shown in figure 3(b) and (c), even if the received power is less than threshold it makes the decision that a single target exists within the circle of the range. So we need to find another

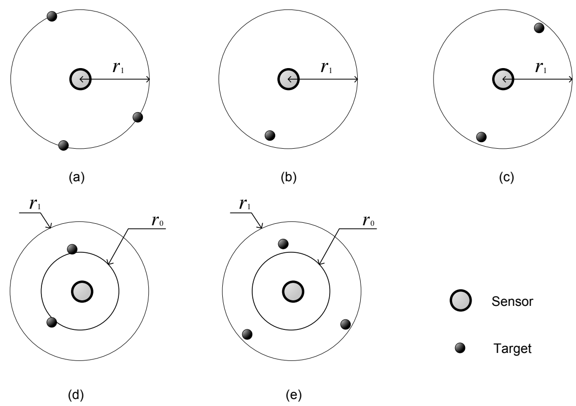


Fig. 3. Choosing the threshold. (a) Threshold power when maximum number of targets are 3. (b) No detection of targets within the range (error). (c) No detection of targets within the range (error). (d) Detection of targets outside of the new range (error). (e) Detection of targets outside of the new range (error)

solution for these errors. With respect to each of the errors in figure 3, we can find the solution or adjustment as follows,

- In order to avoid errors as in figure 3(b) or (c), we adopt a new range ($r_0$) which is shorter than the $r_1$ and it will be explained shortly how to find it. Nevertheless the threshold power remains the same, so in the case of figure 3(b) or (c), the sensor does not make the decision of detection and it becomes true with the range $r_0$ because targets will be located outside of the range boundary and received power is also less than the threshold power. These targets will be attached to the neighboring sensors. We can find the range $r_0$ as shown in figure 4 according to (1) such that the strength of the signal from a single target at $r_0$ and the strength of the signal from each of the 3 targets at $r_1$ received at a sensor must be the same. We may call $r_1$ reference range. According to (1), if $d_0 = 1$, $\alpha = 2$ and $N = 3$, then the following condition must be satisfied.

$$\frac{1}{{r_1}^2} + \frac{1}{{r_1}^2} + \frac{1}{{r_1}^2} = \frac{1}{{r_0}^2}, \quad r_0 = \frac{r_1}{\sqrt{3}} \tag{2}$$

So now we do not encounter the error type as in figure 3(b) or (c).

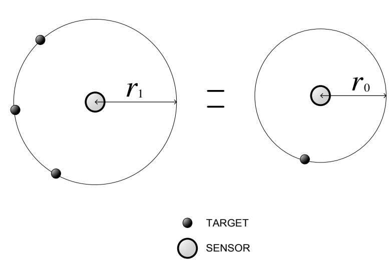


Fig. 4. Range of a sensor

- Once we have new range of $r_0$, we encounter other types of error as in figure 3(d) or (e). Figure 3(d) shows that even though two targets are outside of the range, the sensor makes decision of detection because it receives power greater than the threshold, which is an error. The situation in figure 3(e) does not occur frequently in practice. In this case a sensor falsely makes decision of the detection too because it receives power greater than threshold as in the case of figure 3(d). If we relate it to the resolution of the sensor, we can avoid errors as in 3(d) and (e). We assume that not more than one target can exist within the reference range, $r_1$. After these two modifications, we do not encounter errors as in figure 3 any more, but if there are more than one target together within the range $r_1$ we can not resolve it and make a detection error. That is why we may call the reference range $r_1$ resolution of the sensor. We can not resolve more than one target within the range $r_1$. The resolution is directly related with threshold power when the maximum number of targets is set to a constant. The resolution capability of a sensor is decreasing when the reference range $r_1$ is increasing. The resolution of a sensor does not directly rely on the range of a sensor, $r_0$. The reference range $r_1$ is increasing when the maximum number of targets are increasing under the condition of the constant range $r_0$, which means the resolution capability of a sensor worsens as the maximum number of targets increases. The threshold power signal is increasing when the maximum number of targets increases for a constant resolution of a sensor.

### *B. Threshold Power*

An acoustic sensor sends the signal to the fusion center that there is a target around itself, (it does not have exact information of the location of a target but certainly inside of the circle with the radius of the range, $r_0$), when it makes a decision of detection according to the decision rules. Threshold power ($\Delta_1$) is defined as the received power from a single target which is located on the boundary of the range $r_0$ while no noise power is considered. This will construct the first step of the ADMAN. Once a sensor receives the power greater than the threshold, it exclusively detects a target inside the boundary circle of the range of itself. More difficult situation forms another step of the algorithm with introduction of another threshold power ($\Delta_2$). As shown in figure 5, $\Delta_2$ is defined as the received power from a single target which is located on the circle of radius $\sqrt{2}r_0$

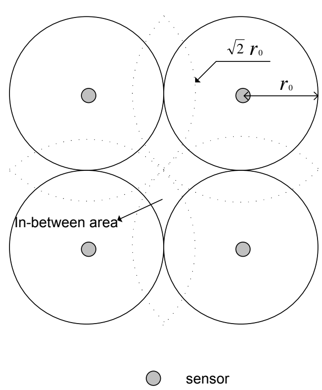


Fig. 5. Neighboring four sensor ranges

distance. When a target is located in *in-between* area (the *in-between* area is defined as the area that does not belong to any circle of the range), this other threshold is necessary to resolve the location of target. No more than one sensor is supposed to receive power greater than $\Delta_1$, but more than one sensor may receive power between $\Delta_1$ and $\Delta_2$ according to the algorithm. So if the strength of the received power is between $\Delta_1$ and $\Delta_2$, a target is most probably located in in-between area of four neighboring sensors. In this case a target is attached to the sensor that has the maximum received power among neighboring sensors. Finally the sensors do not pay attention to any received power that is less than $\Delta_2$. The advantage of the ADMAN is that it can cope with any variation in the number of targets. In lots of the literature, the pattern of variation of the number of targets are limited and restricted in their applied examples so that it is somewhat predictable for detecting the varying number of targets in time steps [6], [7]. ADMAN shows superiority when the number of targets vary dramatically. The ADMAN without any decision rule is summarized by the following table. The GLRT approach to *composite hypothesis testing* for the ADMAN is explained in the following section.

**Summary of ADMAN**

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Field of interest is full of deployed sensors as in figure 1 and each sensor is identified with number from the left bottom to right top. The measurements of the sensors are scanned from 1 to $N$. Given $r_0$, $r_1$, $\Delta_1$, $\Delta_2$, $N$ and $X$, where $r_0$ is the range of the sensor, $r_1$ is the reference range of the sensor, $\Delta_1$ and $\Delta_2$ are the thresholds ($\Delta_1 > \Delta_2$), $N$ is the total number of sensors in the field of interest and $X$ is the number of sensors in one row in the field of interest. At any time instant $t$,

1) For $n = 1, 2, \ldots, N$,
   - If $y_{n,t} > \Delta_1$, attach a target to the sensor $n$ which means sensor $n$ believes there is a target within its range of $r_0$.
   - If $\Delta_2 \leq y_{n,t} \leq \Delta_1$, check whether $y_{n,t}$ is from already attached target or not. If so, we attach a target to the sensor that has greatest power among the neighboring sensors, otherwise we attach a target to the sensor $n$.
2) After scanning and target attaching is completed, find out all attachment redundantly in both inside range and in-between area. remove attachment in in-between area.

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## III. Generalized Likelihood Ratio Test (GLRT)

In this section *generalized likelihood ratio test* [8] related to ADMAN is explained as a solution for the *composite hypothesis testing* problem in the detection part. In our problem, the parameter is not known under any of the hypotheses. The primary approaches to hypothesis testing are the classical approach based on the Neyman-Pearson theorem and the Bayesian approach based on minimization of the Bayes risk.

There are two major approaches to *composite hypothesis testing*. One is the *Bayesian approach* which considers the unknown parameter as random variable with prior density function. The other method estimate the parameter by the maximum likelihood method and applies it to the likelihood ratio test, this is the well known, *generalized likelihood ratio test*. Usually GLRT method is more practical and easier to apply rather than Bayesian method which requires the knowledge of prior and more assumptions and multidimensional integrations for the closed form that usually impossible. In this paper we will focus on GLRT. We estimate parameter first with ML method to detect multi targets to be employed in ADMAN.

### *A. Hypotheses*

In this sub section we describe all hypotheses we need to define. At any time step we have three hypotheses. We call them $\mathcal{H}_0$, $\mathcal{H}_1$ and $\mathcal{H}_3$. We combine $\mathcal{H}_0$ and $\mathcal{H}_1$ as $\mathcal{H}_2$. So first hypothesis test is composed of $\mathcal{H}_2$ and $\mathcal{H}_3$. If $\mathcal{H}_2$ is selected then we go to the next hypothesis test to decide if $\mathcal{H}_1$ or $\mathcal{H}_0$. Under $\mathcal{H}_3$ we have a target within the boundary circle of the range of the sensor, under $\mathcal{H}_1$ we have target in *in-between* area and under $\mathcal{H}_0$ we do not have to pay attention because a target is located out of the sensor's range so some other sensor will be related and attached to the target at that time step. This two stage hypothesis testing procedure can be summarized as in figure 6. So *multiple hypotheses testing* problem is modified to

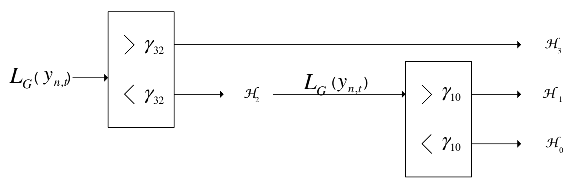


Fig. 6. Procedure of decision of detection in hypotheses testing performed with respect to every sensor.

two steps of single hypothesis testing problem. Referring to (1), we can rewrite received power of sensor $n$ at time instant $t$ as follows,

$$y_{n,t} = \theta_{n,t} + v_{n,t}, \quad n = 1, 2, \ldots, N \tag{3}$$

,where $\theta_{n,t} = 10 \log_{10} \left( \sum_{k=1}^{K} \frac{\Psi_k d_0^\alpha}{|\mathbf{r}_n - \mathbf{l}_{k,t}|^\alpha} \right)$.

All hypotheses are described as follows,

$$\mathcal{H}_3 : \theta_{n,t} = \theta_{n,t}^3 > \Delta_1$$

$$\mathcal{H}_2 : \theta_{n,t} = \theta_{n,t}^2 \leq \Delta_1$$

$$\mathcal{H}_1 : \theta_{n,t} = \theta_{n,t}^1, \quad \Delta_2 < \theta_{n,t}^1 < \Delta_1$$

$$\mathcal{H}_0 : \theta_{n,t} = \theta_{n,t}^0 \leq \Delta_2$$

, where $\Delta_1$ and $\Delta_2$ are threshold powers as defined previously. The decision regions and probabilities are shown in figure 7 and 8. The decisions are performed as in the following two steps. If $\mathcal{H}_2$ is decided in the first test, we will go to the second

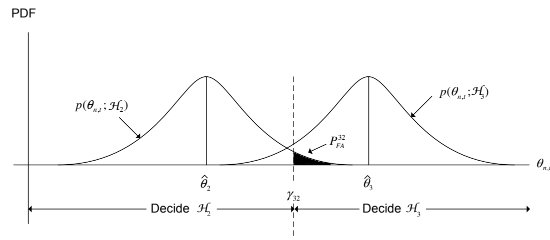


Fig. 7. First hypothesis testing.

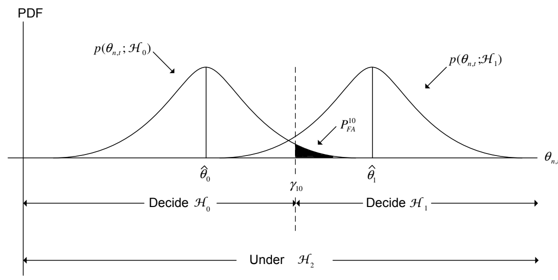


Fig. 8. Second hypothesis testing.

hypothesis test for complete decision as in the summarized tables.

## IV. ESTIMATION OF STATES FOR DETECTED TARGETS

This section is devoted to localization of targets which are already detected by ADMAN. Targets are dynamically moving according to state space equation as follows [9],

$$\mathbf{x}_t = \mathbf{G}_x \mathbf{x}_{t-1} + \mathbf{G}_u \mathbf{u}_t \tag{14}$$

where $\mathbf{x}_t = [\ddot{x}_{1,t} \;\; \ddot{x}_{2,t} \;\; \dot{x}_{1,t} \;\; \dot{x}_{2,t} \;\; x_{1,t} \;\; x_{2,t}]^\top$ is a state vector which indicates the acceleration , velocity, and position of the target in a two-dimensional Cartesian coordinate system, $\mathbf{G}_x$ and $\mathbf{G}_u$ are known matrices defined by

$$\mathbf{G}_x = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ T_s & 0 & 1 & 0 & 0 & 0 \\ 0 & T_s & 0 & 1 & 0 & 0 \\ \frac{T_s^2}{2} & 0 & T_s & 0 & 1 & 0 \\ 0 & \frac{T_s^2}{2} & 0 & T_s & 0 & 1 \end{pmatrix}$$

$$\text{and } \; \mathbf{G}_u \mathbf{u}_t = \mathbf{u}_t = \begin{bmatrix} \omega_1 & \omega_2 & 0 & 0 & 0 & 0 \end{bmatrix}^\top,$$

**First Hypothesis Testing**

To perform GLRT we have to find the estimates of parameters by the maximum likelihood estimate (MLE) method as,

$$\hat{\theta}_3 = y_{n,t}, \text{ but if } y_{n,t} \le \Delta_1, \text{ take } \hat{\theta}_3 = \Delta_1. \tag{4}$$

$$\hat{\theta}_2 = y_{n,t}, \text{ but if } y_{n,t} > \Delta_1, \text{ take } \hat{\theta}_2 = \Delta_1. \tag{5}$$

next, GLRT decides $\mathcal{H}_3$ if

$$L_G(y_{n,t}) = \frac{p(y_{n,t}; \hat{\theta}_3, \mathcal{H}_3)}{p(y_{n,t}; \hat{\theta}_2, \mathcal{H}_2)} > \gamma_{32} \tag{6}$$

where with the variance of noise, $\sigma$ ,

$$p(y_{n,t}; \hat{\theta}_3, \mathcal{H}_3) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y_{n,t} - \hat{\sigma}_3)^2\right]$$

$$p(y_{n,t}; \hat{\theta}_2, \mathcal{H}_3) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y_{n,t} - \hat{\sigma}_2)^2\right]$$

Then (6) also can be easily shown as,

$$\ln L_G(y_{n,t}) = \frac{1}{2\sigma^2}(2\hat{\theta}_3 y_{n,t} - 2\hat{\theta}_2 y_{n,t} - \hat{\theta}_3^2 + \hat{\theta}_2^2) > \ln \gamma_{32} \tag{7}$$

Given certain probability of false alarm, $P_{FA}^{32}$, it is defined and related with threshold, $\gamma_{32}$ as follows,

$$\begin{aligned} P_{FA}^{32} = P(\mathcal{H}_3|\mathcal{H}_2) &= Pr\{y_{n,t} > \gamma_{32}; \mathcal{H}_2\} \\ &= \int_{\gamma_{32}}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{1}{2\sigma^2}(t - \hat{\theta}_2)dt\right] \\ &= Q\left(\frac{\gamma_{32} - \hat{\theta}_2}{\sigma}\right) \end{aligned} \tag{8}$$

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$T_s$ is sampling period (second), $\sigma_i$ is uniformly distributed in $[-W_{max}\ W_{max}]$ $(m/s^2)$. We are interested in the location of targets, so only location part of state will form the measurement as in (1). Our goal is to estimate $x_{1,t,k}$ and $x_{2,t,k}$ given estimated $\hat{n}_{1:K,t}$, identities of sensors attached by $k$ targets, we believe to have found in previous ADMAN. We address estimating algorithm as *maximum likelihood Monte Carlo* method. The first step is generating uniform particles within the range of attached sensors given $\hat{n}_{1:K,t}$. Then we select the particle according to maximum likelihood function. *maximum likelihood Monte Carlo* method is summarized in the last table.

## V. Simulation

In this paper one example of jointly detection and estimation technique is introduced. All independent targets are dynamically moving as presented in previous section. The maximum number of targets is 3 and initially two targets are moving in the filed of interest. The other target spontaneously appears in 4 sampling time instants delay. The first target lasts 100 time sequence and disappear, second target lasts 96 time sequence and disappear and the last one lasts 4 time sequence more since first target disappeared, 8 time sequence more after the second target disappeared.

**Second Hypothesis Testing**

After finding MLEs of $\theta_1$ and $\theta_0$ as following,

$$\hat{\theta}_1 = y_{n,t}, \text{ but if } y_{n,t} \leq \Delta_2, \text{ take } \hat{\theta}_1 = \Delta_2 \tag{9}$$

$$\hat{\theta}_0 = y_{n,t}, \text{ but if } y_{n,t} > \Delta_2, \text{ take } \hat{\theta}_0 = \Delta_2 \tag{10}$$

the GLRT decides $\mathcal{H}_1$ if

$$L_G(y_{n,t}) = \frac{p(y_{n,t}; \hat{\theta}_1, \mathcal{H}_1)}{p(y_{n,t}; \hat{\theta}_0, \mathcal{H}_0)} > \gamma_{10} \tag{11}$$

where with the variance of noise, $\sigma$ ,

$$p(y_{n,t}; \hat{\theta}_1, \mathcal{H}_1) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y_{n,t} - \hat{\sigma}_1)^2\right]$$
$$p(y_{n,t}; \hat{\theta}_0, \mathcal{H}_0) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y_{n,t} - \hat{\sigma}_0)^2\right]$$

Then (11) also can be easily shown as,

$$\ln L_G(y_{n,t}) = \frac{1}{2\sigma^2}(2\hat{\theta}_1 y_{n,t} - 2\hat{\theta}_0 y_{n,t} - \hat{\theta}_1^2 + \hat{\theta}_0^2) > \ln \gamma_{10} \tag{12}$$

Given certain probability of false alarm, $P_{FA}^{10}$, it is defined and related with threshold, $\gamma_{10}$ as follows,

$$\begin{aligned} P_{FA}^{10} = P(\mathcal{H}_1|\mathcal{H}_0) &= Pr\{y_{n,t} > \gamma_{10}; \mathcal{H}_0\} \\ &= \int_{\gamma_{10}}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{1}{2\sigma^2}(t - \hat{\theta}_0)dt\right] \\ &= Q\left(\frac{\gamma_{10} - \hat{\theta}_0}{\sigma}\right) \end{aligned} \tag{13}$$

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The sensors are uniformly deployed on two dimensional rectangular area of interest. The reference range, $r_1 = 30$, $[m]$ therefore the range, $r_0 = \frac{r_1}{\sqrt{3}} = 17.3205$ $[m]$. The threshold powers, $\Delta_1 = 10000/{r_0}^2 = 33.33$ $[J/s]$=15.2288 $[dB]$ and $\Delta_2 = 10000/(\sqrt{2}r_0)^2 = 16.6667$ $[J/s]$=12.2185 $[dB]$. $W_{max}$ is equal to 4 $[dB]$, $\Psi_1 = \Psi_2 = \Psi_3 = 4$ $[dB]$, $d_0 = 1$ $[m]$, $\alpha = 2$, $v_{n,t}$ is Gaussian noise with zero mean and variance of 0.03 $[J/s]$. Starting points of each targets are (200,200), (0,100) and (200,50) and the number of particles is 3000. After deploying sensors, we give identifications to all sensors with numbers from left bottom to right top. According to ADMAN any target detected will be attached specific sensor exclusively identified by its number. The simulation shows the result of detection of targets with time in figure 9 and estimation of tracked locations of targets in figure 10.

## VI. Conclusions and Future Work

The MLMC (Maximum Likelihood Monte Carlo) method is introduced for the localization of targets that are detected by ADMAN. When applying ADMAN, GLRT (Generalized Likelihood Ratio Test) is adopted for the solution of the composite hypothesis testing for detecting unknown and varying number of targets with highly non-linear motion in the acoustic sensor networks. Experiments showed that the ADMAN with MLMC to be robust and accurate through the long time sequence of

**Summary of *MLMC* method**

After detection step is accomplished we have estimated sensors attached to $K$ targets as $\hat{n}_{1:K,t}$. At any time instant $t$,

1) Generate particles uniformly within the range of each attached sensor.
   - $l^i_{1:K,t} \sim U(\cdot|\hat{n}_{1:K,t})$, $i = 1, 2, \ldots, P$, $P$ is the number of particles and one particle has the information of the number targets detected at time instant $t$.
2) Compute the *likelihood function* of each particle and choose the particle that has the *maximum likelihood* for the estimates of locations of targets. Likelihood function is given as

$$F_{y^{1:K}_{\hat{n}_{1:K,t}}}(Y^{1:K}_{\hat{n}_{1:K,t}}|\hat{n}_{1:K,t}, l^i_{1:K,t}) \tag{15}$$

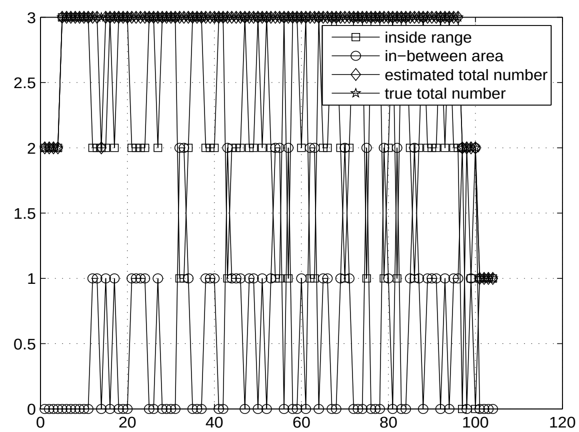


Fig. 9. Number of Targets in Time

trajectories where unknown number of targets keep on varying. Even though we used Markov Chain dynamic state model for hidden states, the solution is not restricted to the models. Proposed approaches can alleviate the complexity of solving the problems of unknown and varying multi-target in sensor networks. Even if a number of targets are to be tracked, increased complexity of the problem is not remarkable adopting proposed approaches in this paper. If we want to resolve multiple targets when they are very close, we can increase the resolution of the sensor at the expense of the increased number of sensors deployed in the field of interest. When we have more sensors in the field of interest, the range can be much smaller that mainly decides the resolution of the sensors. Due to the non-sequential or memoryless property of MLMC, it is significantly more robust than *particle filter* through the longer time duration and highly non-linear dynamic trajectory of the target. The influences of changing parameters, for example the range $r_0$ and threshold power, $\Delta_1$ and $\Delta_2$ will be investigated. If we divide region of interest into appropriate sectors we can save sensor resources in the future.

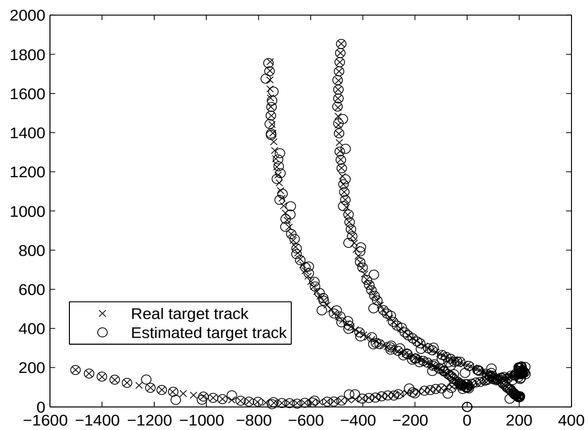


Fig. 10. Localization of detected targets. Dots show the estimated locations of targets.

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