분산 선배열 소나와 레이다를 이용한 표적 연관 기법

Association Algorithm for the Distributed Passive Linear Arrays and the Radar

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ABSTRACT

PLA(Passive Linear Array) system has been primarily utilized to detect and track underwater targets, such as submarines. This system has difficulty in distinguishing between underwater targets and surface ships in a dense target environment. And a single-PLA system does not provide target state observability. At least two PLAs are necessary to observe a track uniquely. To classify and localize the underwater targets effectively, first of all, it is very of importance to discriminate the surface ships in the multi-target environment. These problems can be overcome by the association of distributed PLAs and radars.

In this paper, we present an algorithm to solve the track-to-track association of the heterogeneous data from three PLAs and one radar are noncollocated with known sensor positions. Also, this paper shows the simulation results to verify the proposed algorithm.

주요기술용어(주제어) : Passive Linear Array(수동 선배열 소나), Track-to-Track Association(궤적 대 궤적 연관), Nearest Neighbor Association(최소 근접 연관 기법)

1. Introduction

PLA(Passive Linear Array) system is generally difficult to track and classify the underwater targets of interest in the complex sea[1~3]. This system observes only the line of sight angle for targets[4,5] and does not provide target state observability. At least two PLAs are necessary to observe a track uniquely. In recent years, the surveillance and tracking systems are making use of a variety of sensing devices, such as distributed multiple passive sensors and the radar, to classify and track the underwater targets of interest effectively. In these systems, the track-to-track association problem of the heterogeneous data from the passive sensors and the radar must be solved[6]. Although considerable research has been undertaken in passive bearing track to position track association, those are presently concerned about one radar and one passive sensor, such as ESM(Electronic Support Measure), DF(Direction Finder) and IRST(InfraRed Search and Tracker)[7,8]. The problem

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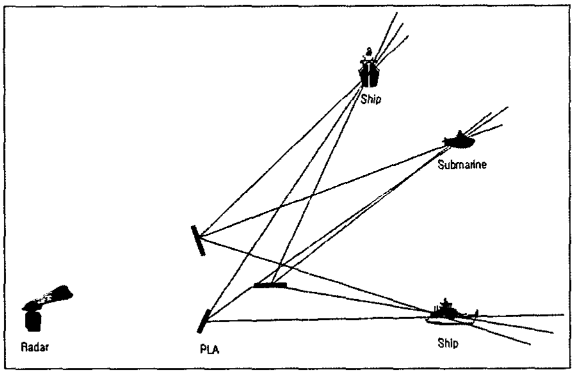
of track-to-track association is how to decide whether tracks from different sensors represent the same target. Here, each sensor has its own target tracking process and has a number of tracks. Then association is performed using one of a number of possible approaches[9]. The NNA(Nearest Neighborhood Association) approach assumes that the estimate closest to the center of the validation gates represents the target. In contrast to the NNA, the JPDA(Joint Probabilistic Data Association) and MHT(Multiple Hypothesis Tracking) use all estimates within the target validation gate. The NNA approach requires minimal computational resources, and it work well in simple situations with low clutter and high SNR(Signal to Noise Ratio) detection.

In this paper, we propose the MMJPA(Maximum Mixed Joint Probability Association) algorithm: the MMJPA algorithm consists of a data alignment, a validation testing, a cost generation, and a solving association matrix. Also, this paper shows the simulation results to verify the proposed algorithm.

2. Sensor Model

It is assumed that the three PLAs and the radar are noncollocated with known sensor positions as



[Figure 1] Arrangement of multi-sensor to multi-target

shown in Fig. 1. Also, it is assumed that each sensor has own target tracking process.

Since the PLA generally estimates bearings and frequencies using narrowband processing and fusion based Kalman filter, the bearing and the tonal frequencies of the target i obtained by the PLAs at time t_s is modeled as follows[10]

$$\begin{aligned} &\beta_{si_s}(t_s) \approx N(\theta_{si_s}(t_s), \sigma^2_{\theta_{si_s}}(t_s)), \quad 0 \le \beta_{si_s} < \pi \\ &\xi^k_{si_s}(t_s) \approx N(f^k_{si_s}(t_s), \sigma_{f^k_{si_s}}(t_s)), \quad k = 1, \cdots, m_{si_s} \end{aligned} \tag{1}$$

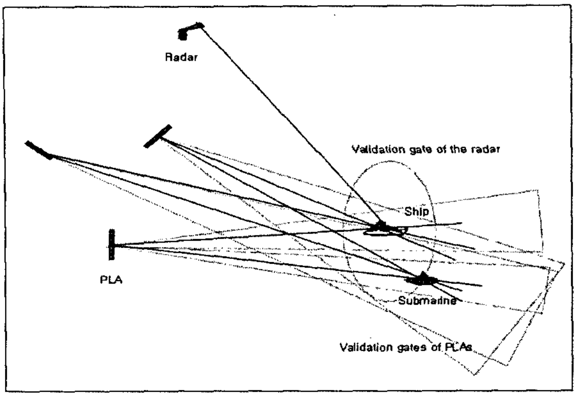
where $\theta_{si_s}(t_s)$, $f^j_{si_s}(t_s)$, $\sigma^2_{\theta_{si_s}}(t_s)$, and $\sigma^2_{f^j_{si_s}}(t_s)$ are the bearing, the kth frequency, the covariance of the bearing, and the covariance of the frequency of target i estimated by the PLA s, respectively. m_{si_s} is the number of frequencies of the target i detected by the PLA s. It is assumed that bearings and frequencies are statistically independent, and that each PLA is statistically independent.

Since the radar measures the azimuth and the range of the target j at time t_R, the state variable $\hat{\mathbb{X}}_{Rj}(t_R|t_R)$ and its covariance matrix $\mathbb{P}_{Rj}(t_R|t_R)$ are estimated by measured data using converted measurement Kalman filter or extended Kalman filter[11,12]. In this paper, we uses converted measurement Kalman filter.

3. Proposed Algorithm

Fig. 2 shows association problem in multi-sensor to multi-target environment. To decide whether tracks from different sensors represent the same target, the problem of track-to-track association must be solved.

If tracks from each PLA represent the same target, these are associated with a track from the radar at the same time. Therefore, it is more efficient that the set of tracks from the three PLAs



[Figure 2] Association problem in multi-sensor to multi-target environment

is associated with the track from the radar, while that tracks from each PLA are individually associated with the track from the radar. And target tonal frequencies provided by the PLAs are important factor to decide a set of tracks for the same target. In this paper, we propose the MMJPA algorithm as shown in Fig. 3.

Generally, the three PLAs and the radar are not synchronized, since the PLAs use a sound wave in water while the radar uses an electromagnetic wave in air. Therefore we can synchronize the radar with the PLAs as follows

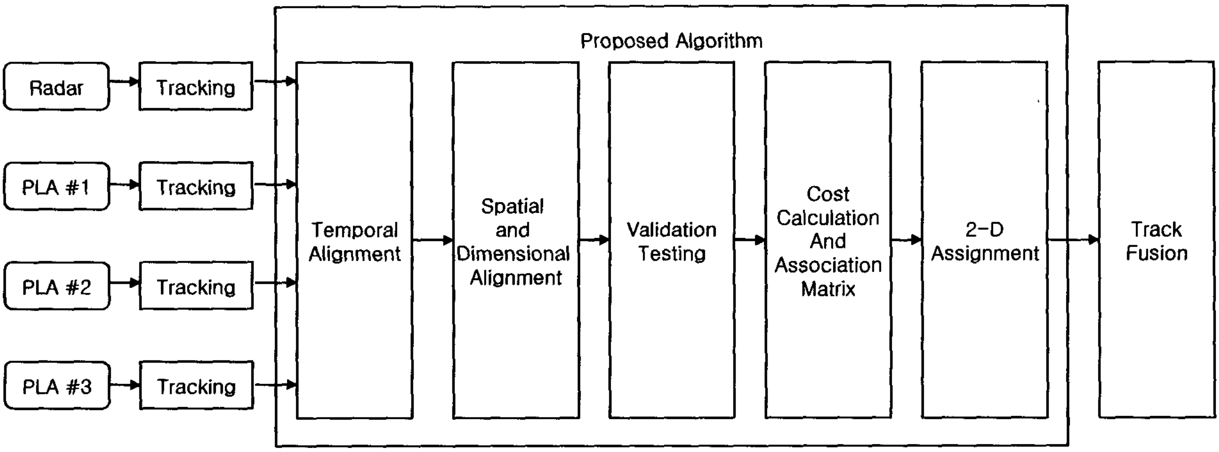
$$\begin{aligned} \hat{\mathbb{X}}_{Rj}(t_s - t_d|t_R) &= \mathbb{F} \cdot \hat{\mathbb{X}}_{Rj}(t_R|t_R) \\ \mathbb{P}_{Rj}(t_s - t_d|t_R) &= \mathbb{F} \cdot \mathbb{P}_{Rj}(t_R|t_R) \cdot \mathbb{F}^T + \mathbb{Q} \end{aligned} \quad (2)$$

where superscript T denotes a transpose. $\mathbb{F}$ is the state transition matrix, and $\mathbb{Q}$ is the plant noise covariance matrix. t_s and t_R are the time of PLAs and the radar, respectively. t_d is the propagation delay of a sound wave in water, given by

$$t_d = \frac{(x_s - x_j(t_R))^2 + (y_s - y_j(t_R))^2}{c} \quad (3)$$

where c is a sound propagation speed in water. (x_s, y_s) is the location of the PLA s, and $(x_j(t_R), y_j(t_R))$ is the position of the target j from the radar at time t_R.

We can test that tracks from the PLAs can be associated with the radar tracks. The statistic test is



[Figure 3] Block diagram of the MMJPA algorithm

$$\Delta^2_{si_sj} = (\theta_{si_s} - \hat{\theta}_{sj})^T(\sigma^2_{\theta_{si_s}} + \hat{\sigma}^2_{\theta_{sj}})^{-1}(\theta_{si_s} - \hat{\theta}_{sj}) < \gamma(\sim \chi^2) \tag{4}$$

where θ_{si_s} is the bearing of the target i from the PLA s, $\sigma^2_{\theta_{si_s}}$ is its covariance. $\hat{\theta}_{sj}$ is the bearing of the target j that is projected by the PLA from the radar, and $\hat{\sigma}^2_{\theta_{sj}}$ is its covariance. If the three PLAs and the radar are synchronized, and if the PLA is located at (x_s, y_s) and is rotated by Φ_s, $\hat{\theta}_{sj}$ is given by

$$\hat{\theta}_{sj} = \cos^{-1}\left(\frac{(x_j - x_s)}{\sqrt{(x_j - x_s)^2 + (y_j - y_s)^2}}\right) - \Phi_s \tag{5}$$

where (x_j, y_j) is the synchronized position of the target j from the radar by eqn. (2).

$\hat{\sigma}^2_{\theta_{sj}}$ can be induced from covariance matrix $\mathbb{P}_{Rj}(t_s - t_d | t_R)$ from the radar.

$$\hat{\sigma}^2_{\theta_{sj}} = \mathbb{H} \cdot \mathbb{P}_{Rj}(t_s - t_d | t_R) \cdot \mathbb{H}^T \tag{6}$$

where

$$\mathbb{H} = \left[\ \frac{-(y_s - y_j)}{r^2} \quad 0 \quad \frac{x_s - x_j}{r^2} \quad 0\ \right].$$
$$r^2 = (x_s - x_j)^2 + (y_s - y_j)^2$$

We denote the set of tracks from the PLAs by

$$Z_{i_1 i_2 i_3} = \{\theta_{1i_1}, \theta_{2i_2}, \theta_{3i_3}\},\ i_s = 0, 1, \cdots, n_s \tag{7}$$

where θ_{1i_1}, θ_{2i_2}, and θ_{3i_3} are selected by eqn. (4), and $i_s = 0$ denotes dummy bearing. It enables us to consider all track associations(including the single and two PLA detections) as 3-tuples.

Since tracks from the PLAs are statistically independent, the likelihood function of the 3-tuple $Z_{i_1 i_2 i_3}$ being the set of tracks from the PLAs that originated from the same target is the mixed probability density function

$$L(\gamma_j) = \Lambda(Z_{i_1 i_2 i_3} | x_j, y_j) = \prod_{s=1}^{3} [P_{D_s} p(\theta_{si_s} | x_j, y_j)]^{1-\delta_{0i_s}} \times [1 - P_{D_s}]^{\delta_{0i_s}} \tag{8}$$

where δ_{0i_s} is the delta function. If $i_s = 0$, $\delta_{0i_s} = 1$, otherwise $\delta_{0i_s} = 0$. P_{D_s} denotes the detection probability of the PLA s.

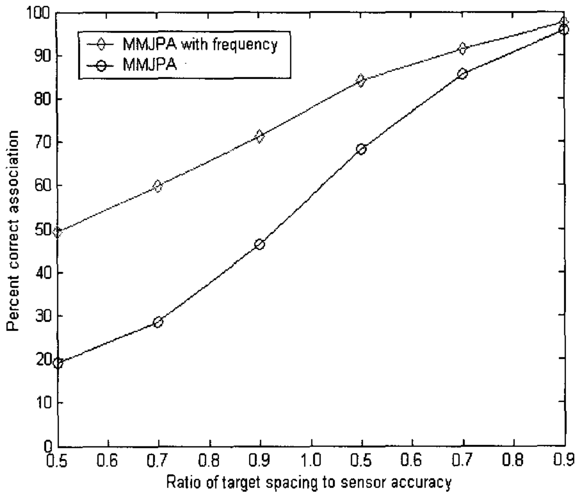
Since the target positions (x_j, y_j) are estimated from the radar, modified mixed joint probability density function can be modified using the eqn. (4), (6), (7) and (8) as

$$L(\gamma_j) = \prod_{s=1}^{3} [P_{D_s} N(\hat{\theta}_{sj}, \sigma^2_{si_s} + \hat{\sigma}^2_{sj})]^{1-\delta_{0i_s}} \times [1 - P_{D_s}]^{\delta_{0i_s}} \tag{9}$$

The tonal frequencies emitted by targets represent one of their inherent characteristics. These can be used to decide available 3-tuples for the same target. But each PLA can detect different frequencies for the same target and it can miss some frequencies in ocean. In case of using the frequencies, it is reasonable that the similarity of the frequencies between targets from the PLAs is used for association with tracks, rather than the pattern of the frequencies is used. To apply the similarity of frequencies, define the binary event variables as follows

$$F_{i_1 i_2 i_3} = \begin{cases} 1, & \text{if } \dfrac{n(f_{1i_1} \cap f_{2i_2} \cap f_{3i_3})}{n(f_{1i_1} \cup f_{2i_2} \cup f_{3i_3})} \geq \eta \\ 0, & otherwise \end{cases} \tag{10}$$

where $n(f_{1i_1} \cap f_{2i_2} \cap f_{3i_3})$, $n(f_{1i_1} \cup f_{2i_2} \cup f_{3i_3})$ are the number of the intersection and union about each f_{1i_1}, f_{2i_2}, f_{3i_3} set, respectively. f_{si_s} is defined by



[Figure 4] Association performance comparison according to normalized PLA accuracy at 100% detection probability

$$f_{si_s} = \{f_{si_s}^{k}\}_{k=0}^{m_{si_s}};\quad i_s = 0,1,\cdots,n_s,\quad s=1,2,3 \tag{11}$$

where n_s is the number of targets detected by the PLA s.

As eqn. (9) and (10), the cost function of the MMJPA is

$$C_{i_1i_2i_3} = B_{i_1i_2i_3} \times F_{i_1i_2i_3} \tag{12}$$

where

$$\begin{aligned} B_{i_1i_2i_3} &= -\log\left(L(\gamma_i)\right) \\ &= \sum_{s=1}^{3}\Bigg[(1-\delta_{i_s})\left(\ln\left(\frac{\sqrt{2\pi}\,(\sigma_{\theta_{si_s}}+\sigma_{\hat{\theta}_{sj}})}{P_{D_s}}\right)\right. \\ &\qquad \left. +\frac{1}{2}\left(\frac{\theta_{si_s}-\hat{\theta}_{sj}}{\sigma_{\theta_{si_s}}+\sigma_{\hat{\theta}_{sj}}}\right)^2\right) - \delta_{i_s}\ln\left(1-P_{D_s}\right)\Bigg]. \end{aligned} \tag{13}$$

In a dense target environment, the track-to-track association problem is to solve an assignment matrix with non-zero element as cost function defined by eqn. (12) or (13). It is equivalent to generalized 2-D assignment problems.

4. Simulation Result

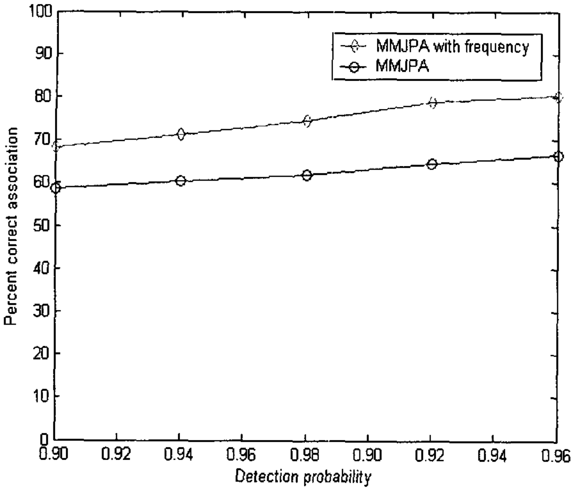
To demonstrate the performance of the proposed algorithm, simulations were performed for three closed target with the known position of the noncollocated the three PLAs and the radar. The target 1 and the target 2 have the similar characteristics of frequencies set, but the target 3 has the different characteristics. Each target has constant velocity of 8 m/s. The performance of the proposed algorithm is measured by the percent of correct associations over 500 Monte Carlo runs.

Figure 4 shows the performance of association versus the normalized bearing accuracy of the PLAs, when the detection probability of the PLAs is 100%. A horizontal axis is the ratio of target separation to the accuracy of the PLAs, and a vertical axis is the percent of correct association.

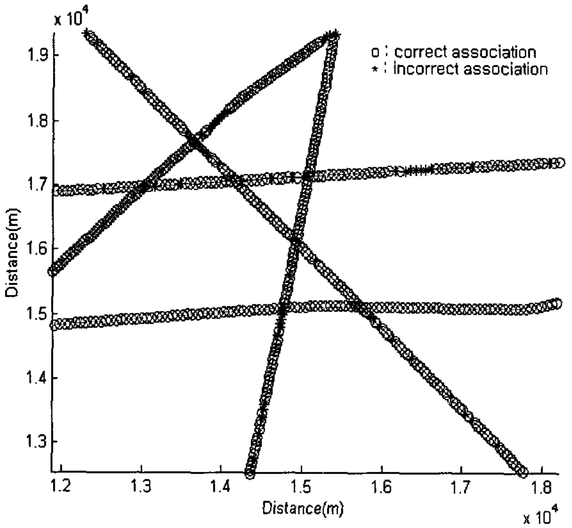
If targets have the similar characteristics of frequency domain, the cost functions defined by eqn. (12) and eqn. (13) show the similar performance. When the normalized accuracy of the PLAs is 0.9, the percent of correct associations is more than 80%. But the cost function defined by eqn. (12) improves the performance, if targets have the different characteristics of frequencies.

In Fig. 5, we see the performance of association versus detection probability of the PLAs, when the normalized accuracy of the PLAs is 0.8. A horizontal axis is the detection probability of the PLAs, and a vertical axis is the percent of correct association. When targets have the different characteristic of frequencies, the cost function defined by eqn. (12) improves the performance.

In Fig. 6, the result is illustrated that the proposed association algorithm has good performance in multi-target environment.



[Figure 5] Association performance comparison according to PLA detection probability at 0.8 normalized PLA accuracy



[Figure 6] Typical association result of proposed algorithm in multi-target environment

5. Conclusions

In this paper, we propose the MMJPA algorithm for the track-to-track association of the heterogeneous data from the three PLAs and the radar. To solve the problem of track-to-track association, we fomulate the assignment matrix using the cost function. This cost function is composed of the mixed joint probability and the similarity of frequencies for the set of tracks from the PLAs and the radar.

The performance of proposed algorithm is demonstrated by a computer simulation in a dense multiple maneuvering target environment.

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