Data Association Approach for Two Dimensional Tracking Based on Bearing-Only Measurements in Clutter Environment

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***Abstract*—This paper mainly studies angle-measurement based data association algorithm to overcome the existing problems in the applications of traditional association approaches for bearing-only target locating and tracking system. First, this paper proposes a fast track initiation approach for the system using a single passive sensor. In this approach, the rules of screening out threatening targets are set by analyzing the characteristics of target motion in two dimensional bearing-only coordinates. And the track initiation of threatening targets is implemented in the shortest time based on a modified heuristic algorithm using these rules. Then, other target tracks are initialized based on a logic-based algorithm in two dimensional bearing-only coordinates as a supplement. At last, by deeply studying different point-track association algorithms and comparing the association effect between JPDA and NNDA in bearing-only coordinate, suitable angle-measurement based association algorithm is presented. As the results, the confirming efficiency of the bearing-only measurements is improved and false tracking with the dense clutter is limited. The application of this algorithm has effectively resolved the track association problem of the bearing-only tracking using a single passive sensor. The application of the proposed approach in a simulation system proves its effectiveness and practicability.**

***Index Terms*—data association, track initiation, bearing-only tracking, passive sensor, NNDA, JPDA**

I. Introduction

Data association is the most important in the multi-target tracking system. For prior knowledge lack of tracking environment and sensor performance limitation itself, measurement inevitably blends with noise. In addition, for single target, multi-measurement existing is possible because of clutter disturbing. So it is necessary to confirm the relation between target and measurement by statistical approach. Moreover, the corresponding relation between measurement and target is destroyed for the uncertainty and randomicity in clutter environment. As the same time, it is very important to establish new target track before it is tracked because early warning tracking system must provide all information of potential target in clutter environment. Therefore, data association technology is very important. Especially, target tracking algorithm application is mainly based on right data association.

The bearing-only tracking using passive sensor is obtaining target motion element by angle-only measurements. Even if the target motion is constant velocity (CV), the target motion expression is very difficult to approximate only by using linear equation in the θ - ϕ (azimuth and pitching) plane. This problem is high nonlinear in substance and target measurement motion takes on higher maneuverability in the θ - ϕ plane. All of these results in a great challenge in data association algorithm application. As yet, this issue resolved has been difficult in maneuvering target tracking domain [1-5]. Traditional multi-station united passive tracking watching system estimates 3-D information based on 2-D measurement. Namely, this system indirectly gets the target position information by using multi-angle intercrossing approach [6, 7]. But, this approach brings more "ghosting" and more computing cost in target association tracking for sensor measuring error itself. At the same time, this approach is limited by the distance demand between the station and the other station. So the target tracking error is enlarged and this approach application value is little. In view of the demands of the concealment and flexibility for passive tracking system, the suited target tracking algorithm based on a single passive sensor is urgent very much. In correlative references [8, 9], some scholar make linear assumption for bearing-only target motion if sampling time of passive sensor is shorter and target confirming precision is higher. Based on it, θ and ϕ of target are regarded as decoupling. From its inspiration, this paper supposes that 2-D bearing-only target motion is linear in sample cycle and tracking estimation is directly based on angle-measurements. Aiming at the bearing-only tracking characteristics, a resolving approach completely based on angle-only measurements is studied by the deeply analysis of point-point association (track initiation) and point-track association in clutter environment.

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II. TRACK INITIATION BASED ON BEARING-ONLY MEASUREMENTS

A. Existing problem and solution

Multi-target track initiation is primary problem of maneuvering target tracking. It is a decision-making link of new target file establishment. For multi-target tracking processing, the right track initiation is key to reduce the burden of track processing and improve maneuvering target tracking effect. Traditional track initiation approach is difficult to find real target quickly and effectively. Moreover, for the lack of distance information, target threatening level can not be reasonably estimated. Taking into account the relevant characteristics of single passive tracking system and high real-time demand in the battlefield, mostly maneuvering target tracking need feedback target track information timely for tracking with scanning system. So taking sequential processing approach，which includes heuristic algorithm and logic-based algorithm [10-13], is primary choice for track initiation in the bearing-only tracking system due to good real-time performance. It is worth noting that those targets which have high attacking velocity as well as small angle between moving direction and sensor axis is potential threatening target. Early warning tracking system need track them closely. This paper presents a track initiation approach completely based on bearing-only measurements from a single passive sensor. First, the rules of screening out threatening targets are set by analyzing the characteristics of target motion in two dimensional bearing-only coordinates, and the threatening targets are initiated by heuristic algorithm based on these new rules. Here, the advantage of fast initiation of heuristic algorithm is made full use to screen out threatening target in θ-φ plane. After limiting the application object of heuristic algorithm, those isolated measurements and candidate tracks which aren't associated must be processed. Therefore, use low-order polynomial to approximate the actual target motion in θ-φ plane so that candidate target track can be confirmed based on a logic algorithm as a supplement. The cooperation of the two approaches makes track initiation more effective and provides a base for determining the threatening level of target in bearing-only tracking system. As the same time, this approach ensures correct track initiation and lower false probability. Approach flow is shown in fig.1.

B. Heuristic rule based on bearing-only measurements

Traditional heuristic algorithm is based on two simple rules, so called velocity and acceleration rules. Inspired by the traditional rules, assume that maximum angular velocity is $\omega_{\max}$ and maximum angular acceleration is $\dot{\omega}_{\max}$ in track initiation phase. So the rules of bearing-only track initiation algorithm are

$$\left\| \frac{r_{k+1} - r_k}{t_{k+1} - t_k} \right\| \le \omega_{\max} \tag{1}$$

$$\left\| \frac{r_{k+1} - r_k}{t_{k+1} - t_k} - \frac{r_k - r_{k-1}}{t_k - t_{k-1}} \right\| \le \dot{\omega}_{\max} (t_{k+1} - t_k) \tag{2}$$

where r_k is bearing-only position vector at sample time k, t_k is sample time.

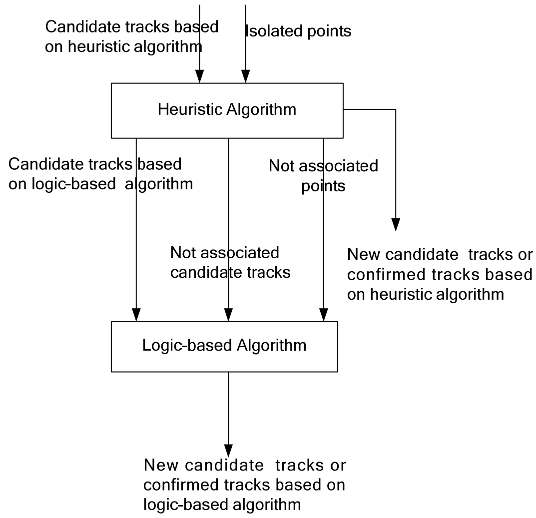

Figure.1 Procedure of track initiation approach

Maximum angular velocity is gotten by making assumption that target moving along tangential direction to observation point. Target is always far from observation point in track initiation phase. Real system must reliably track target at D km away from observation point. D is set by tracking system. According to $v_{\max}$ (maximum velocity of target) and D, $\omega_{\max}$ is gotten easily. $\dot{\omega}_{\max}$ can be gotten based on relevant conditions the same as reasoning. In order to reduce false probability of track initiation, another angular rule is given. Assume that Φ is angle between vector $r_{k+1} - r_k$ and $r_k - r_{k-1}$, namely

$$\Phi = \cos^{-1}\left[\frac{\langle (r_{k+1} - r_k), (r_k - r_{k-1}) \rangle}{\|r_{k+1} - r_k\| \cdot \|r_k - r_{k-1}\|} \right] \tag{3}$$

Angular rule is

$$|\Phi| \le \Phi_0 \tag{4}$$

where, $0<\Phi_0\le\pi$, it is a threshold corresponding to maximum angular change set by tracking system beforehand.

To satisfy real-time demand, measurement sequence from continuous three sample circles is taken into previous rules in this system. If meeting these rules, target track is initiated successfully. But these rules aren't rigorous enough.

In bearing-only tracking system, fast initiation of threatening target is very important and track processing system must pay more attention to. This paper gives relevant rule to confine application area of heuristic algorithm. Namely, only use heuristic rule to initiate those targets which have higher radial velocity and

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threatening level. Under the circumstances, position change of target measurement is fixed or angular velocity of target measurement is lower in θ-φ plane. So introduce a rigorous rule into heuristic algorithm application. Depict the rule as follow:

If the angle between moving direction and observation axis is less than β, it is threatening attention target. Maximum angular velocity of target, namely

$$\omega_T = \tan^{-1}\left(\frac{v_{\max} * \sin\beta}{D * 10^3}\right) \tag{5}$$

Then additional rule is

$$\left\| \frac{r_{k+1} - r_k}{t_{k+1} - t_k} \right\| \le \omega_T \tag{6}$$

After the new rule with primary threatening level decision is introduced, the advantage of fast track initiation of heuristic algorithm is made full use to lock the threatening target. It not only improves warning ability of surveillance and tracking system but also limit false track extension due to non-rigorous rules.

C. Logic-based track initiation based on bearing-only measurements

The foregoing heuristic algorithm mainly aims at those threatening targets. But its initiation condition is rigorous after all and ordinary target can not be initiated effectively. As a supplement, this paper adopts logic-based algorithm to find them. Logic-based track initiation in θ-φ plane depicts as

1) Isolated bearing-only measurements which aren't associated by heuristic algorithm will be used to establish new candidate track. By angular velocity rule, measurements in next cycle are put into association decision.

2) Candidate track from step 1 is linearly extrapolated. Regard extrapolative point as associated center and make association decision for bearing-only measurements from next cycle. If some candidate track isn't associated with every measurement, those candidate tracks are terminated.

3) Those candidate tracks which aren't associated by heuristic algorithm can be associated using step 2. If associated, this candidate track is put into logic-based candidate track files.

4) For every candidate track including three or more measurements, it is extrapolated by using second-order polynomial. Then make relevant associated decision according to the extrapolative point. The rest can be deduced up to the N-th step by analogy. Confirm target track by comparing the relation between innovation and threshold at last. For time *k(k=N)*, bearing-only measurement sequence corresponding to candidate track *m* is

$$\{ z_{1,\rho(1,m)}, z_{2,\rho(2,m)}, \ldots, z_{N,\rho(N,m)} \} \tag{7}$$

where $\rho(k, m)$ depicts as measurement number corresponding to temporary track *m*.

Define cumulative innovation as

$$J^*(m) = \sum_{k=1}^{N} [z_{k,\rho(k,m)} - \hat{z}_{k,m}]^T (R_k)^{-1} [z_{k,\rho(k,m)} - \hat{z}_{k,m}] \tag{8}$$

where $\hat{z}_{k,m}$ is position estimation of temporary track through polynomial fitting, namely

$$\hat{z}_{k,m} = \sum_{j=0}^{n_x} \hat{a}_j^m (k\Delta T)^j / j! \tag{9}$$

where $\hat{a}_j^m$ is polynomial fitting coefficient.

Proved in reference [14], statistical value $J^*(m)$ is chi-square (χ^2) distribution with $Nn_z - n_x$ degree of freedom（n_x is polynomial fitting order）. If statistical value $J^*(m)$ satisfy test of threshold γ, which is gotten based on χ^2 distribution with $Nn_z - n_x$ degree of freedom, namely

$$J^*(m) \le \gamma \tag{10}$$

Then, this candidate track is target track. It turn into tracking phase. For fast track initiation, this paper set continuous decision cycle as 4.

III. FEASIBILITY STUDY OF BEARING-ONLY DATA ASSOCIATION ALGORITHM

A. Nearest Neighbor Data Association (NNDA）

NNDA [15, 16] is an early simple association algorithm. It helps to ensure the real-time demand of passive sensor target tracking. This approach associates the nearest neighbor measurement away from the tracking target in statistical view. This statistical distance is defined as weighed norm of innovation vector, that is

$$d_k^2 = \tilde{\boldsymbol{z}}_{k|k-1}^T \boldsymbol{S}_k^{-1} \tilde{\boldsymbol{z}}_{k|k-1} \tag{11}$$

where $\tilde{\boldsymbol{z}}_{k|k-1}$ is filter innovation, $\boldsymbol{S}_k$ is innovation covariance matrix, d_k^2 is norm of error vector.

The radical meaning of NNDA is uniquely choosing the nearest measurement away from target as associated object to estimate target state. For easy realization and little computing cost, it is applied to the tracking systems which have the high *SNR* and the little target density. But when the measurement density is tremendous or multi-target association gate intercrossing each other, the nearest measurement not always come from the tracking target. Therefore, NNDA's anti-jamming capability is not so good and this approach easily brings false association.

B. Joint Probabilistic Data Association(JPDA)

JPDA [17-19] is advancing extending algorithm from PDA [20] (Probabilistic Data Association). It resolves the bug of false tracking in the application of PDA algorithm in the high maneuvering target density environment. This algorithm always is considered as one of the most perfect association approach. But comparatively, its computing cost is high because the association hypothesis event number between target and measurement is exponential

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expanded. Moreover, the distance between the two targets is very near. It is possible to bring bias and aggregation of track. Flow chart of this algorithm is shown in figure 2. The key technology of this algorithm lists the following

1) *Association gate*

$$A^t(k) \equiv \left\{ \frac{z}{[z-\hat{z}^t(k\mid k-1)]S^t(k)^{-1}[z-\hat{z}^t(k\mid k-1)]'} \le g_t^2 \right\} \tag{12}$$

Where, t=1,2,…,N, $\hat{z}^t(k|k-1)$ is the position estimation of target t at k; $S^t(k)$ is error covariance matrix of the measurement t at k.

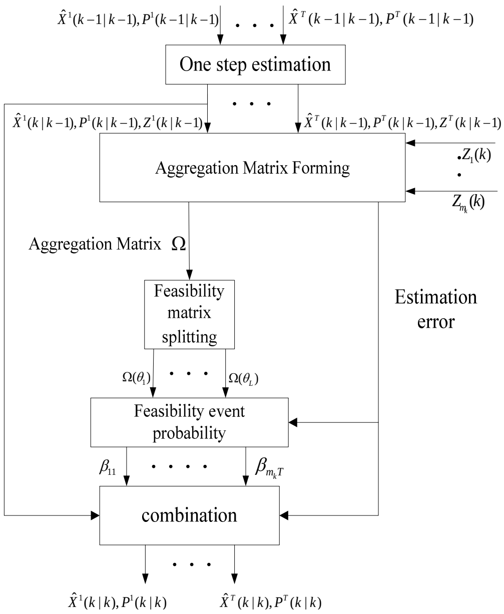

Figure 2. JPDA algorithm flow chart

$$S^t(k) = E\left\{[z-\hat{z}^t(k\mid k-1)][z-\hat{z}^t(k\mid k-1)]'\right\} \tag{13}$$

where g_t^2 denotes gate value.

If and only if the target measurement involves in the target association gate, it is regarded as valid measurement, or rejected. Assume that there are m_k valid measurements involving in N target-gates. Those measurements in the association gate are regarded as following association standby.

2) *Clustering matrix*

If consider that clustering matrix (or confirmed matrix) have m_k rows and $N+1$ lines, clustering is defined as the most aggregate of conjoint tracking gate. All of targets are divided into different groups according to different clustering. There is a binary element matrix of clustering matrix which associates each of these groups all the time. Clustering matrix is defined as follows:

$$\Omega=(\omega_{jt}),\ \ j=1,2,...,m_k;\ t=0,1,...,N \tag{14}$$

where ω_{jt} denotes that measurement j whether or not is contained by association gate.

$$\omega_{jt}=\begin{cases}1 & \text{If } Z_j(k) \text{ is in the association gate}\\ 0 & \text{or else}\end{cases} \tag{15}$$

where, $j=1,2,...,m_k$, $t=1,2,...,N$, and t=0 means that no target exist and correspondingly all line elements of Ω are 1. In this time, any measurement originates from clutter or falsehood.

3) *Feasibility Event*

Feasibility event is produced by clustering matrix. Assume association event

$$\theta_{jt} = \left\{\text{valid measurement } Z_j(k) \textit{ comes} \text{ from the target } t\right\} \tag{16}$$

Where, $j=1, \ldots, m_k$, $t=1,2,\ldots,N$.

When t=0, θ_{j0} denotes measurement $Z_j(k)$ coming from clutter or noise. Note association event posterior probability

$$\beta_{jt}=P\left\{\theta_{jt}|Z^k\right\} \tag{17}$$

B_{jt} is association probability. It is probability of association event appearance.

Define joint association event

$$\theta=\bigcap_{j=1}^{m_k}\theta_{jt_j} \tag{18}$$

Joint association event θ may represent matrix:

$$\hat{\Omega}(\theta)=\left[\hat{\omega}_{jt}(\theta)\right] \tag{19}$$

where

$$\hat{\omega}_{jt}(\theta)=\begin{cases}1 & \theta_{jt}\subset\theta\\ 0 & \textit{or else}\end{cases}, \tag{20}$$

If satisfying two conditions as follows, joint association is defined as feasibility event θ:

- Every measurement only comes from a headspring, target or clutter, namely:

$$\tau_j(\theta)=\sum_{t=0}^{T}\hat{\omega}_{jt}(\theta)=1 \qquad j=1,2,...,m_k \tag{21}$$

- Every target only has a measurement, that is

$$\delta_t(\theta)=\sum_{j=1}^{m_k}\hat{\omega}_{jt}(\theta)\le 1 \qquad t=1,2,...,N \tag{22}$$

For feasibility event θ, corresponding matrix $\hat{\Omega}(\theta)$ is referred to as feasibility matrix. It is gotten by splitting clustering matrix， that is scanning Ω and only choosing a "1" in every row as feasibility matrix element. Except for the first line, every line of feasibility matrix only has a "1". $\delta_t(\theta)$ is defined as target detecting indicator and $\tau_j(\theta)$ is defined as measurement indicator. Then clutter number is:

$$\Phi(\theta)=\sum_{j=1}^{m_k}[1-\tau_j(\theta)] \tag{23}$$

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4) Feasibility Event Probability and Association Probability Calculation

The sum of joint association event is L at k. Condition Probability, that is

- If clutter model is Poisson distribution, then

$$P(\theta_i|Z^k)=\frac{\lambda^{\Phi}}{c'}\prod_{j=1}^{m_k}[N_{t_j}(Z_j(k))]^{\tau_j}\prod_{t=1}^{T}(P_D^t)^{\delta_t}(1-P_D^t)^{1-\delta_t} \quad (24)$$

- Else if clutter model is uniformity distribution, then

$$P(\theta_i|Z^k)=\frac{1}{c}\frac{\Phi!}{v^{\Phi}}\prod_{j=1}^{m_k}[N_{t_j}(Z_j(k))]^{\tau_j}\prod_{t=1}^{T}(P_D^t)^{\delta_t}(1-P_D^t)^{1-\delta_t} \quad (25)$$

Where, c and c' are unitary element.

$$N_{t_j}(Z_j(k))=N\left(Z_j(k);Z_j^t(k|k-1),S_j^t(k)\right) \quad (26)$$

Where, N denotes normal distribution.

Finally, association probability is:

$$\beta_{jt}=\sum_{i=1}^{L}P\left\{\theta_i|Z^k\right\}\hat{\omega}_{jt}(\theta_i) \quad (27)$$

Where, $j=1,...,m_k;t=1,...,T$

The probability of invalid measurement originating from target t is:

$$\beta_{0t}=1-\sum_{j=1}^{m_k}\beta_{jt}, \quad j=1,...,m_k;t=1,...,T \quad (28)$$

5) State Estimation

$$\hat{X}^t(k|k)=\sum_{j}^{m_k}\beta_{jt}\hat{X}_j^t(k|k) \quad (29)$$

IV. Multi-model Filter Design for bearing-only target tracking

In order to test data association effect, this paper must present an acceptable filter to estimate bearing-only target state. As far as concerned, tracking filter directly processes based on bearing-only state. On the other hand, even if the target motion is CV, the target motion is very difficult to express by using linear equation in the θ - ϕ plane. This problem is high nonlinear in substance and target motion takes on higher maneuverability in θ - ϕ plane. For its higher target maneuverability and the variety of structure and parameter existing in target motion model, single-model adaptive filter is difficult to accurately recognize these varieties in time so that inaccurate model and false tracking inevitably appear. Multi-model filter use several suited model to approximate the real target motion. Among them each model has a potential maneuvering mode. Random maneuvering of target is depicted as random hopping among models. By designing filter composed of several model, accordingly carry them into effectively execution for maneuvering target tracking. Thus, improving tracking performance is naturally shown. In polar coordinate, redefine state variable as

$$X=[\theta \quad \varphi \quad \dot{\theta} \quad \dot{\varphi}]' \quad (30)$$

Aiming at the bearing-only tracking characteristics, resolving approach by using IMM [21-23] filter completely based on bearing-only measurements is chosen because IMM is regarded as the first multi-model algorithm up to application value [24]. By analysis of algorithm framework, measurement information utilization of IMM exists in not only filtering estimation but also model probability. And IMM can adaptively adjust model with model probability change. Simultaneity, this algorithm has modularization characteristic. Through different application, filtering module can adopt all kinds of linear and nonlinear filtering algorithm. Finally, efficiency is improved in virtue of each filtering module working side by side in this algorithm. In this paper, model selection only limits to CV and CA because there isn't so good performance for CT in polar coordinate and value of ω is difficult to grasp. The research indicates that common motion can be approximated by certain combination of CV and CA.

In this paper, there is an IMM filter composed of 4 models used to track. These models depict as: There are different Q matrix for model 1-model 3, which are CV whose process noise coefficient respectively are 1, 0.1, 0.01. And model 4 is chosen as CA whose process noise coefficient respectively is 0.1. Initial model probability matrix

$$\mu_0=[1/4 \quad 1/4 \quad 1/4 \quad 1/4] \quad (31)$$

Model transition probability matrix

$$P=\begin{bmatrix}0.97 & 0.01 & 0.01 & 0.01\\ 0.01 & 0.97 & 0.01 & 0.01\\ 0.01 & 0.01 & 0.97 & 0.01\\ 0.01 & 0.01 & 0.01 & 0.97\end{bmatrix}$$

V. Simulation

For getting more clear result, track initiation will be simulated firstly in order to test its distinguishing ability and fast ability in clutter environment. At last, set environment to test the final effect of data association and track system as a whole.

A. Track initiation simualtion

Introduce guide line for simulation judgment [25].

1) False probability of track initiation (FP)

$$FP=\sum_{i=1}^{N}f_i/\sum_{i=1}^{N}n_i \quad (32)$$

where N is simulation number based on Monte-Carlo. N=30 in this paper. f_i is false track number and n_i is initiated track number as a simulation.

2) Correct initiation probability (C_j)

$$C_j=\frac{\sum_{i=1}^{N}l_{ij}}{N} \quad (33)$$

where l_{ij} represents if target j is initiated correctly

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in the *i*-th Monte-Carlo simulation. Correct is 1, or 0.

TABLE I. INITIAL STATES OF THE TARGETS IN CARTESIAN COORDINATE

Target	Model	Velocity	X	Y	Z
1	CT	714	9000	3100	2400
2	CV	530	11000	2000	150
3	CV	400	12000	3100	800
4	CA	450	10000	-2000	1000
5	CV	500	12000	100	800
6	CV	490	9000	1200	800
7	CV	500	15500	1000	900
8	CV	480	10000	0	100
9	CV	450	10000	3000	100
10	CA	500	9100	1100	1800

There are ten targets in simulation environment. Their movements are CA, CV and CT respectively. Process noise is white Gaussian noise and noise coefficient is 1.5m. Initial states of the targets list as tab.1 (position and velocity unit are m and m/s respectively.). There, acceleration of target 4 and target 10 are 100m/s^2 and 43m/s^2 respectively. Figure out bearing-only measurement in polar(θ - ϕ) coordinate based on these target tracks in Cartesian coordinate. Assume clutter density $\lambda = 5.21*10^{-5}$/mrad^2 （Clutter number is Poisson distribution. Clutter is scattered as uniform distribution. ） and measurement noise coefficient is 1.5mrad. Note that angle unit is one thousandth of radian, namely mrad. There, D=10km, T=1.5s, $v_{\max}$ =1km/s, $a_{\max}$ =100m/s^2 and threshold test significance level $\alpha = 0.01$. Moreover, Heuristic angular rule is $\pi / 2$ and threatening area is that the angle between target moving direction and sensor axis is less than 15° . In order to test speed of track initiation, this simulation is based on 6 sample cycle. Typical clutter environment is shown in fig.3. Effect of track initiation is shown in fig.4. Based on 30 times Monte-Carlo simulation, false track probability with different clutter density is shown in fig. 5. Correct track initiation probabilities of the targets as follow

C_1=83.3%, C_2=90.0%, C_3=86.7%, C_4=90.0%,
C_5=80.0%, C_6=83.3%, C_7=86.7%, C_8=86.7%,
C_9=90.0%, C_{10}=86.7%.

B. The track effect of data association system.

Here, three target intercrosses in polar coordinate in order to increase tracking difficulty. Target motion is shown Fig.6 (The first is in Cartesian coordinate and the second is in bearing-only coordinate).

Assume that measurement noise is white Gauss noise.

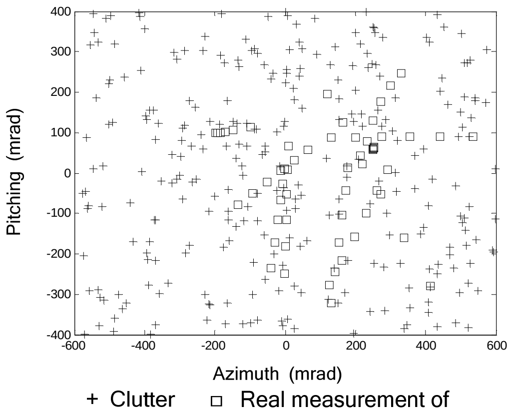

Figure 3. Bearings-only measurements in clutter environment

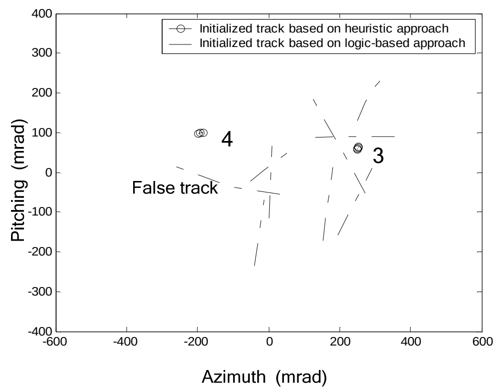

Figure 4. Effect of track initiations

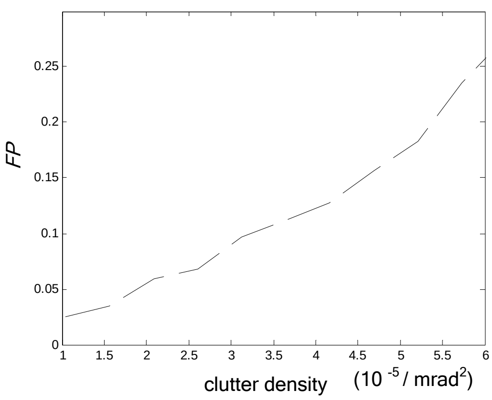

Figure 5. False track probabilities based on the clutter density

TABLE II. COMPARING THE PERFORMANCE BETWEEN JPDA AND NNDA IN WHOLE SAMPLING TIME

Algorithm	Target 1		Target 2		Target 3	
coordinate	*azimuth (rad）*	*pitching (rad）*	*azimuth (rad）*	*pitching (rad）*	*azimuth (rad）*	*pitching (rad）*
JPDA (RMSE)	0.0490	0.0057	0.0160	0.0058	0.0096	0.0057
NNDA (RMSE)	0.4883	0.0636	0.0172	0.0066	0.1975	0.0644

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Noise coefficient is 10mrad. At the same time, assume that sampling circle T=1.5s, sensor detecting probability P_D=0.99, $\lambda=4\times10^{-5}$/mrad^2 and gate coefficient P_G=0.99 here.

Tracking results are shown in Fig.7-Fig.9 by 30 steps Monte-Carlo simulation. They are performance contrast between NNDA and JPDA. For Y-axis, the first is azimuth RMSE and the second is pitching RMSE. X-axis is sampling number. Comparing the performance between JPDA and NNDA in whole sampling time is shown in Tab.2.

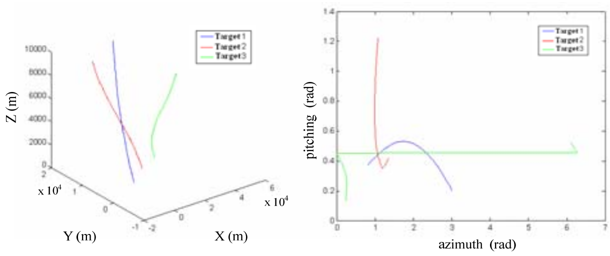

Figure 6. Target track

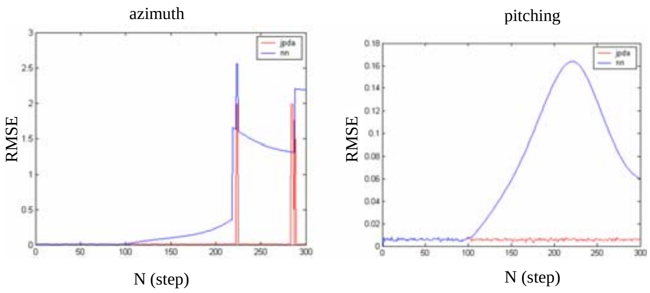

Figure 7. Comparing the association effect between JPDA and NNDA for target 1

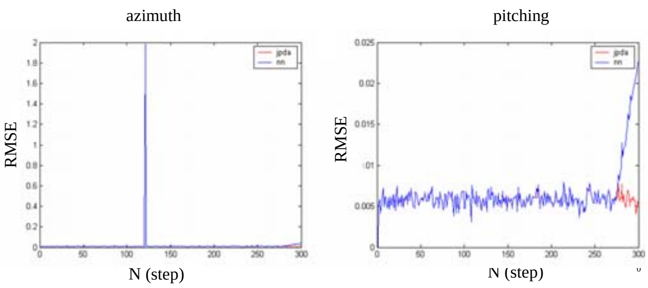

Figure 8. Comparing the association effect between JPDA and NNDA for target 2

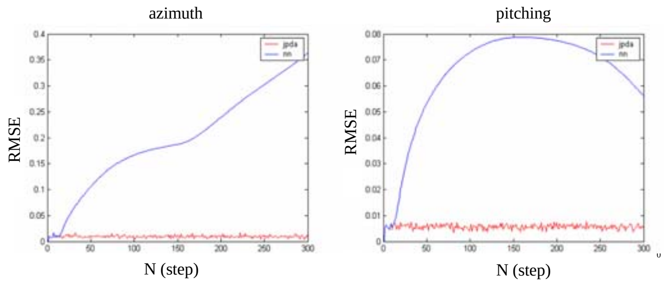

Figure 9. Comparing the association effect between JPDA and NNDA for target 3

VI. CONCLUSION

Simulation of track initiation approach in this paper shows that its fast initiation function is very outstanding and it is well suited for the single passive sensor system. Target 4 and 10 are pre-set threatening target. They are initiated in three cycles. But note that this approach is hard to distinguish low velocity target from threatening target. In order to establish detailed threatening level, area and grey information from passive sensor might be used as a supplement.

According to simulation result of whole data association system and application of actual ship-borne infrared system, adopting JPDA as data association is suitable for bearing-only tracking system using passive sensor. Whereas, its performance takes on not so good comparing with performance in Cartesian coordinate. Moreover, JPDA is very high need for target detecting probability, sampling time and clutter density etc. Unsuitable value might lead to missing tracking. This paper presents part of referenced experience values of bearing-only tracking system with a single passive sensor by deeply simulation and analysis, listed as follow

Choose target detecting probability as high as possible. When $P_D\geqslant0.85$, tracking performance is acceptable.

Choose sampling circle as little as possible. When sampling circle $T\leqslant1.8$s, tracking effect is acceptable.

When noise coefficient $\delta\leqslant10$mrad, tracking effect is acceptable.

Choose clutter density as little as possible. When clutter density $\lambda\leqslant6\times10^{-5}$/mrad^2, tracking probability is acceptable.

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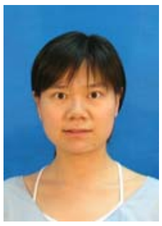

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