A Novel Track Initiation Method for Track Splitting and Merging

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***Abstract*—A novel efficient method is proposed for the splitting and merging problems of track initiation, an important issue of multiple target tracking. Tack initiation demands that the method should determine the existence and initial state of a target quickly and correctly. There is no doubt that the high density of clutters (false alarm), large measurement errors and missing measurements deteriorate and complicate the track initiation. There are two primary shortcomings for the conventional track initiation methods dealing with the issues mentioned above: (i) they cannot exclude the turbulences of the clutters, (ii) they cannot estimate the initial state for a new confirmed track/target. Based on the MHT (multiple target tracking) principle and modified logic-based track initiation method, our new method can deal with the splitting and merging problems deriving from high density of clutters, large measurement errors and missing measurements; it can determine the target's existence and estimate its initial state with the least squares method. What's more, our method is fully automatic and requires no manual input of any kind for initializing and tuning any parameter. The simulation results indicate that the proposed method performs well for track initiation.**

Keywords—multiple target tracking; track initiation; splitting; merging; multiple hypotheses tracking; modified logic-based method; clutters.

I. INTRODUCTION

MTT (Multiple Target Tracking) plays an important role in many fields of engineering, such as surveillance, computer vision, sensors network, computer security and robot [1, 2]. Targets arise randomly in space and time, persist for a random length of time, and then cease to exist; the sequence of states that a target follows during its lifetime is called a track. We always view MTT as an association and estimation problem with one or more sensors of various types (e.g., cameras, radar, laser and sonar) which can obtain measurements originating from targets.

Many sensors operate in a track-while-scan mode [3], so filtering techniques joined with data association algorithms have been developed to sequentially estimate the target tracks using uncertain origin relationship between estimated states and observations. However, many tracking techniques require estimation of the targets' initial state, number of existing targets, and validation of the estimated tracks, which are challenging tasks in the presence of heavy clutters and large noise measurements. Therefore, track initiation is the primary problem of MTT system. The initial state includes the relative position or absolute position, the relative velocity or absolute velocity, and so on. Track initiation has been an active research area and various methods are published in literature. These methods can roughly be classified as sequential methods and batch processing methods [4]. In particular, four popular track initiation methods are investigated, namely, the heuristic method, the logic-based method, the Hough transform method, and the modified Hough transform method. While the former two methods are sequential and widely used in radar and sonar tracking, the latter two methods are batch techniques that are often used in image processing and video tracking.

No matter what track initiation methods, the most common studies are the applications where the number of targets is constant and known during the track initiation stage. However few studies tackle the problems that track splitting and merging events occur during their track initiation stage, which is the main focus of this paper. In the multi-target tracking applications, which provides the motivation for our method, these types of track splitting and merging events are quite common. And most track initiation methods operate in the ideal environment, such as clutters are relatively less, the detection probability is relatively high, and the sensor accuracy is very high. If we cannot deal with track splitting and merging events, the target tracking would be easy to fail (the false alarm probability will increase, the detection probability of a track will decrease, and we cannot find the

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true target). Therefore, track splitting and merging is significant for the track initiation.

The track splitting and merging during the track initiation stage is different from the track splitting and merging during the target tracking stage [2, 5]. The problems of track splitting and merging during target tracking stage derive from the uncertain relationship between targets and measurements. In other words, there are more than one measurements in the valid predicting area of the confirmed track; but one confirmed track/target only generates at most one measurement per scan, and one measurement only has originated from one source. The phenomenon may appear that one confirmed track is associated with some measurements, which is called track splitting during the target tracking stage. The track splitting during the track initiation stage is similar to that during the target tracking stage. But there still are some differences, which focus on the characteristics of the tracks themselves: the tracks (confirmed tracks) during the target tracking stage have relatively accurate state and covariance, but the tracks (feasible tracks) during the track initiation stage do not. The feasible tracks may originate from a target or clutters, and then the uncertain relationship between the measurements and the feasible tracks is relatively large. So it is difficult to determine whether it is a true track originating from a target, or to estimate its accurate initial state with less measurement information.

MHT (Multiple Hypotheses Tracking) can deal with the problems of track splitting during the target tracking stage [6]. Because of the similarity, the track splitting during the track initiation stage may also be tackled by the MHT principle. It creates a feasible track for every possible association in the valid predicting area. With more measurements updating the feasible tracks subsequently, the probability of right association case of a target will be significantly larger than those probabilities of wrong association cases (false alarm). Then we can prune the tracks of low probability, and only retain the tracks of high probability. There are some advantages for the method based on the MHT principle. It can obtain the true track of a target (the track includes almost all the measurements originating from the target). So the estimated accuracy will be satisfying, if we estimate the initial state and covariance matrix with the measurements originating from the target. But there are also some flaws for the MHT principle: it creates so many false tracks, which increases the computational burden, especially in the presence of a lot of clutters and large noise measurements.

Track merging is the inverse process of track splitting, but currently, the track merging method is based on the experience, and it lacks enough mathematical proof or theory.

For the problems mentioned above, mainly based on the MHT principle, we propose the new track initiation method for the track splitting and merging problems.

The structure of this paper is shown as follow. Section II gives a brief description of the problems of track initiation when there are a lot of clutters in the valid predicting region, namely, the track splitting and merging during track initiation stage. Section III introduces some important issues about our new method. We propose our new method in the section IV. The simulation and analyses in Section V show a notable improvement in the performance of our new method in the presence of clutters and large noise measurements. Finally, Section VI summarizes the main conclusions and results of the paper.

II. The Problems of Track Initiation

Track initiation is to determine the presence or not, initial state and covariance for a target, so it is the first and important step for the target tracking. If the track initiation process performs well, target tracking process can quickly reach the steady state, and target trajectories will not fluctuate sharply. If the track initiation process performs poorly, the trajectories would diverge, leading to losing the target.

In general, there are two major factors that affect the track initiation process: one is the track initiation methods, the other is the environment factors and the sensor itself factors, such as clutter density, detection probability of a target and measurement errors of sensors.

A. Track Initiation Methods

Four popular track initiation methods have been introduced above. The issue discussed in this paper is that in the clutter environment and large measurement errors, we should correctly find the track of a target, and estimate its initial state in real-time, namely, we have to deal with the track splitting and merging problems.

In this paper, the sequential track initiations are used for real-time requirement. In the sequential methods, there is not a method which has the absolute advantages, and only in the specific application, one method may have its unique advantages. For example, in the case of high measurement accuracy of a sensor, the heuristic method is more efficient than the logic-based method, but in the case of low measurement accuracy, the logic-based method performs better. In order to deal with the more complex tracking environment, this paper adopts the logic-based method, but for the standard logic-based method, some important improvements have been made for our new method, which will be described in detail later.

B. Environment Factors and Sensor Factors

There are many factors belonging to environment factors and sensor itself factors, such as the clutter density, the detection probability, the measurement errors of sensors, and the data rate.

The clutter density reflects that the statistical characteristics of the background clutters. We can view the clutter density in another perspective, namely that the probability ratio: the probability of noisy measurements falling into the valid predicting area to that of clutters. The larger the ratio is, the larger the clutter density is. If the clutter density is excessive large so that the detection probability of a track decreases, false alarm increases sharply, and eliminating the false tracks becomes more difficult.

The detection probability of sensors described here reflects the target detection ability of a sensor. P_{DT} denotes the detection probability of a target ($P_{DT} \leq 1$). In per scan of a sensor, $P_{DT} < 1$ implies that all the measurements may not include the measurement originating from the true target, or that the target may not be detected by the sensor, which would decrease the detection probability of a track. $P_{DT} = 1$ implies that the target is certain to be detected in per scan. In the conventional track initiation methods, always assume that the detection probability of a target is 1 or close to 1, which reduces the complexity of track initiation problems to some extent. And in the practical engineering applications, such ideal conditions are difficult to meet.

The measurement errors reflect the measurement accuracy of a sensor. The measurement errors are relatively large, namely the measurement factors should not be neglected compared with the movement factors. Reference [7] introduces the relationship between the movement factors of a target and measurement factors of a sensor, and that their tradeoff also affects the performance of track initiation method. It proposed an important parameter of the ratio of the sensor measurement error factors to the target movement factors.

$$\frac{\sigma_l}{v_{\max} \cdot T} \quad \geq \quad 1 \tag{1}$$

where σ_l is the length of the major axis of the 0.9 confidence ellipse with respect to the measurement error covariance matrix, $v_{\max}$ is the target max speed, and T is the sampling period. The measurement errors would be not neglected compared to the movement factors of a target, if (1) holds. So when determining the gate criterions during track initiation stage, we need to consider the relationship between the measurement error factors of sensors and movement factors of a target.

The gate criterions in this paper are determined by the method in [7], during the track initiation stage.

$$\gamma \quad = \quad v_{\max} \cdot k \cdot T + \sigma_l, \quad k = 1,2,3 \tag{2}$$

where γ is the gate threshold, k is the scan interval number between continuous two association. Reference [7] denotes that the threshold determined by (2) can ensure that the probability is more than 0.9, namely we would be about 90% confident that the measurement originating from the target falls into its valid predicting area (assuming that the target is detected).

C. The Relationship Between Measurements and Feasible Tracks

The track initiation methods can also be classified as two categories in other perspective: measurement-oriented methods and target-oriented methods. There is no essential difference between the two categories. But their description and program implementation are different from each other. In general, we can distinguish the two categories in the follow perspective: whether one measurement can be shared by multiple feasible tracks, or whether one feasible track can associate with multiple measurements. Even though we assume that one target only generates at most one measurement, we do not know the right association relationship.

As shown the Fig.1, when a confirmed track has been determined, and there are multiple measurements in the valid predicting area, PDA (Probabilistic Data Association) can deal with this uncertain association problem [9], during the target tracking stage. If two tracks cross or overlap and there are measurements in their common valid predicting area, JPDA (Joint Probability Data Association) can deal with this problem [10]. However, if there are some measurements in the common valid predicting area during track initiation stage, PDA/JPDA performs poorly for this case. PDA/JPDA assigns the probabilities of measurements based on the weighted probability distribution of the relationship between the measurements and tracks. But during the track initiation stage, the feasible track cannot obtain the relatively accurate and reliable state and covariance matrix. So if we deal with those problems with PDA/JPDA method, the result is not satisfying with low confidence level. Namely, we cannot deal with the uncertain relationship by probabilistic methods during the track initiation stage.

MHT method provides a good solution for the problem mentioned above. MHT can effectively handle the uncertain relationship between measurements and feasible tracks by making hypothetic tracks (track splitting). Track splitting can include all the measurements which originate from a target. So, splitting method can increase the detection probability of a track. But while we obtain the true track of a target, it also creates a lot of false tracks, namely that, the false alarm probability increases too. So after the splitting process, we need another steps or processes to decrease the number of false tracks: the bounded value of N and track merging. What we need to emphasize is that the merging process includes the pruning process. The main purpose of merging process is to decrease the number of false tracks, so in the target merging process, the true track originating from a target should not be pruned, and the false tracks should be pruned as soon as possible.

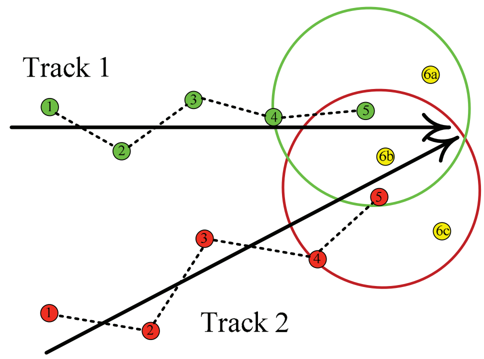

Fig. 1. The relationship between measurements and confirmed tracks. The number denotes the time, the green points denote track1 measurements, the red points denote track2 measurements, and black line denotes the motion direction of targets. The green circle means the valid predicting area of track1, and the red circle means that of track2. The yellow point 6a, 6b, 6c are the measurements at time 6. The point 6a only is in the valid predicting area of track1, the point 6b is in the common valid predicting area, and the point 6c only is in the valid predicting area of track2. For this case, the JPDA method can effectively deal with the uncertain association relationship.

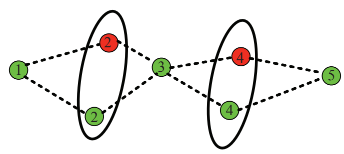

Fig. 2. Two tracks can merge into one track.

Track merging is the inverse process of track splitting, as shown the Fig.2. If there are great similarities between two confirmed tracks, we can merge these two similar tracks into one track, for the case that the track merging results should not deteriorate the track initiation. So some certain conditions should be met before the track merging process performs. The track merging conditions will be discussed in detail later.

III. THE IMPORTANT ISSUES OF THE NEW METHOD

Assume that a target moves along a line with the constant velocity. The measurements of target position only are detected, and the measurement information includes the clutters from background. No additional information can be used to distinguish the measurements from targets or clutters. The measurements originating from the target only depend on the current target state, and the state variable is assumed to be Gaussian distribution, as shown the follow formula.

$$z_k = H \cdot x_k + w_k \tag{3}$$

where x_k is the target state, w_k is the system process noise, and z_k is the measurement information (position information).

It should be noted that in the underwater application, the sensor returns polar information (ranger r and bearing θ) and that a new reconstruction measurement is converted from the Polar coordinates to the Cartesian coordinates. The transformation is

$$\begin{bmatrix} x^1 \\ x^2 \end{bmatrix} = \begin{bmatrix} r\cos(\theta) \\ r\sin(\theta) \end{bmatrix} \tag{4}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{5}$$

where x^1 and x^2 are the position components of the estimated state and the measurement quantity in the Cartesian coordinate system. The statistic characteristic of w_k is also needed to compute again by the UT transform method [8].

As for the sensor, the measurement error matrix R_k is known, and we assume that the detection probability of a target is also known. Based on the value of R_k (the measurement error covariance matrix in the Polar coordinate system), we can obtain the value of σ_l.

$$\sigma_l = \max\{eig(R_k)\} \tag{6}$$

For the distribution information about clutters, both the number and the positions of clutters are assumed to be random and statistically independent from scan to scan. In particular, the number of clutters in each scan is assumed to have Poisson distribution, i.e.

$$p_{Nc}(m) = \frac{\lambda^m}{m!}e^{-\lambda} \tag{7}$$

where λ is the expected number of clutter points. The location of these clutter points is assumed to be uniformly distributed in the total observation area of sensors.

A. *The Rules of a New Confirmed Track*

Considering the real-time requirements, modified logic-based track initiation method is used in this paper. We modify the gate threshold rule for the harsh environment, as shown in the section II. What's more, the parameter M is 5, N is 8. Namely, if there are not less than M measurements meeting the gate threshold rule during not more than N scans, there is a confirmed track determined.

As shown the Fig.3 and Fig.4, we give two examples for illustrating the confirmed tracks. The time that the first track costs is relatively short, and the second is relatively long. The measurements which form a confirmed track may originate from a track or clutters.

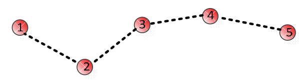

Fig. 3. It costs a relatively short time to form a confirmed track.

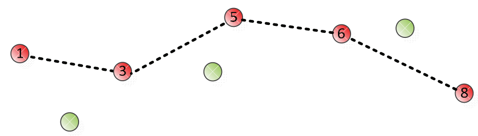

Fig. 4. It costs a relatively long time to form a confirmed track. The number means time, red points originate from the target or clutters, and the green points mean that there is no measurement meeting the gate threshold rule at time 2, 4, 7.

B. *Estimating the Initial State*

The least squares method is used to estimate the initial state and covariance matrix for a new confirmed track.

After analyses and simulations, we use the least squares method to estimate the initial state. We assume that X is $n \times 1$ state vector. In general, we cannot get the true value of X directly, but we can get the noisy measurement information of linear combination of some components of X. Then Z_i is the measurement at time i, we have

$$Z_i = H_i X + V_i \tag{8}$$

where Z_i is the $m \times 1$ dimension measurement vector, H_i is the $m \times n$ measurement matrix, and V_i is the $m \times 1$ noise vector. If there are M measurements, then

$$\begin{aligned} Z_{t1} &= H_{t1}X + V_{t1} \\ Z_{t2} &= H_{t2}X + V_{t2} \\ &\cdots \\ Z_{tM} &= H_{tM}X + V_{tM} \end{aligned} \qquad 1 \le t1 < \ldots < tM \le N \tag{9}$$

Then we get the measurement formula:

$$Z = HX + V \tag{10}$$

where $Z = \begin{bmatrix} Z_{t1} \\ Z_{t2} \\ \cdots \\ Z_{tM} \end{bmatrix}$, $H = \begin{bmatrix} H_{t1} \\ H_{t2} \\ \cdots \\ H_{tM} \end{bmatrix}$, $V = \begin{bmatrix} V_{t1} \\ V_{t2} \\ \cdots \\ V_{tM} \end{bmatrix}$ and $E(VV^T) = R = Diag(R_{t1}, R_{t2}, \ldots, R_{tM})$. X is the state vector of a target at time tM. Z and V are expanded vectors whose dimension is $(Mm) \times 1$, and H is $(Mm) \times n$ matrix. What's more, if the transition matrix of the state is A from time k to $k+1$ in the discrete system, we have

$$H_{ti} = A^{ti-tj}H_{tj} \tag{11}$$

If the rank of H is m, then $H^T H$ is a positive definite matrix. So we estimate X by least squares method.

$$\hat{X} = (H^T H)^{-1} H^T Z \tag{12}$$

The initial covariance matrix is shown as follow.

$$PX = (H^T H)^{-1} H^T R H (H^T H)^{-1} \tag{13}$$

C. *Track Splitting*

If the clutter density is large (there are multiple measurements in the valid predicting area), the splitting method is need for this harsh environment. Based on the MHT principle, we need to create a feasible track for every possible association.

As shown the Fig.5, there are two points (measurements) in the valid predicting area of the track, then we should create two feasible tracks for the two possible associations. Even though one of them is a false track, information is not enough to distinguish these two tracks. Track splitting increases the false tracks, but one of them must be the true track, which is main purpose of track splitting. As for the false tracks, we can prune them by the bounded value of N and track merging.

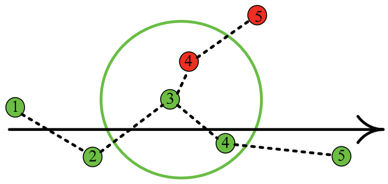

Fig. 5. Track splitting. One track splits into two tracks. At time 4, there are two measurements in the valid predicting area, so we need to create two feasible tracks based on the MHT principle.

D. *Track Merging*

If (i) the two confirmed tracks are formed simultaneously, (ii) their states are close to each other, and (iii) their most measurements overlap (more than $M/2$), then these two confirmed tracks meet the track merging requirements.

There are many cases for the track merging, but they can be divided into two categories. Namely, at the same time, whether the two confirmed tracks share the same measurement? If yes, then the shared measurement is viewed as the measurement of the new track (after merging); if not (the two confirmed track have their own measurements; or, only one confirmed track has a measurement, but the other has no measurement), we should combine the two measurements into one measurement, as shown the Fig.6 and 7.

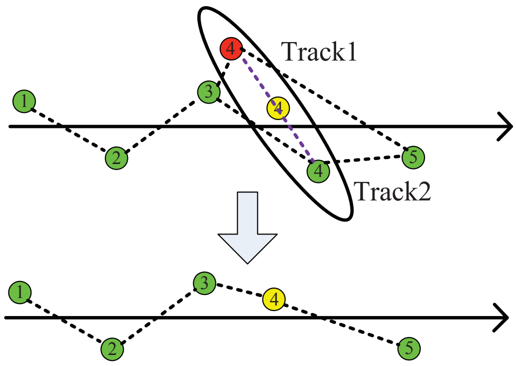

Fig. 6. Track merging. It should merging the R4 and G4 into one point, because the two tracks have high similarities. The Y4 is the merging result of R4 and G4.

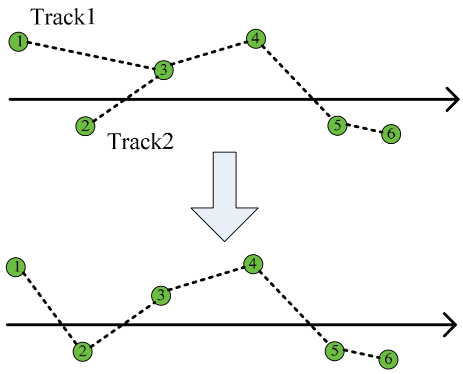

Fig. 7. Track merging. Track1 has no measurement at time 2, and Track2 has no measurement at time 1. Then after merging, new track has measurements from track1 and track2.

IV. The New Method

In this section, we summarize the major steps of the proposed track initiation method for the track splitting and merging problems.

Step 1: Obtaining measurements. Determine whether there are feasible tracks. If not, then skip to step 6, create new feasible tracks. If yes, then skip to step 2, update the feasible tracks. Skip to step 2.

Step 2: Measurement updating. Based on the MHT principle, we associate every feasible track and every measurement in its valid predicting area, and update the feasible tracks. If a feasible track is updated by measurements (it is associated with any measurement in its valid predicting area), we should update some parameters about this feasible track: the number of all measurements association $N_a = N_a + 1$, the number of valid measurements association $N_v = N_v + 1$, and determine the gate threshold again. If a feasible track is not updated (there is no measurement in its valid predicting area), then $N_a = N_a + 1$, but the value of N_v doesn't change, and determine the gate threshold again. Skip to step 3.

Step 3: Confirming the track. If $N_a \geq N$ and $N_v \geq M$, a new confirmed track is formed. And if $N_a \geq N$ and $N_v < M$, then those measurements cannot form a confirmed track (they don't meet the quantity requirements for a new confirmed track), and we should terminate and delete those measurements in advance. Skip to step 4.

Step 4: Estimating the initial state and covariance. If a new confirmed track is formed after step 3, the least squares method is used to estimate its initial state and covariance matrix. Skip to step 5.

Step 5: Track merging. We should merge the tracks which meet the requirements of the track merging, and estimate the initial state and covariance matrix of the new track again. Skip to step 6.

Step 6: Creating new feasible tracks. If there are residual measurements, then we should create a feasible track for every residual measurement. And set the parameters for a new feasible track: the value of N_v is 1, N_a is 1, and determine the gate threshold.

Step 7: Waiting next measurements. Skip to step 1.

As shown the Fig.8, it is the flow diagram.

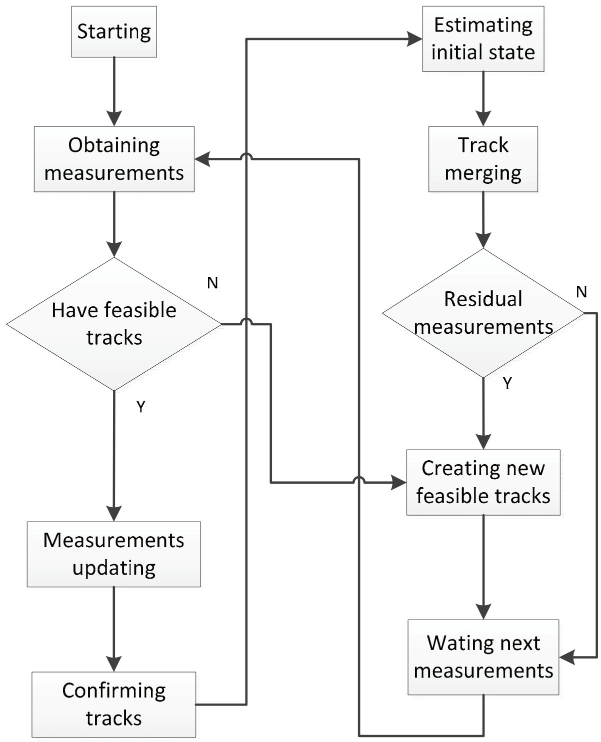

Fig. 8. Flow diagram

V. SIMULATIONS AND ANALYSES

In this section, some simulations and analyses will be made to verify the performance of our new track initiation method for the track splitting and merging problems. Targets are very difficult to be tracked in the underwater environment, because sonar data rate is low, clutter density is large, and the detection accuracy of the sonar is not enough high with respect to the target movement. Assume that we track a target in a two-dimensional plane. This simulation covers a time span of N scans ($N \times T$ seconds).

The parameters of this simulation environment are shown as follow.

The sensor: active sonar. The active sonar can obtain the position (range and bearing) of a target.

The sampling period: 12 seconds.

The measurement errors: the standard deviation of range measurement is 0.015 multiplying by the true distance; the standard deviation of bearing measurement is 1 degree.

The detection area: a circle area of the radius 9000m.

Detection probability of a target: 0.9.

The number of targets: 4.

The positions of targets: they are located in the four quadrants, and far apart from each other. The distance from the sonar to targets is between 6000m to 9000m.

The clutter density: $10^{-6}/m^2$.

The targets speed: 5m/s, uniform linear motion.

As shown the Fig.9, one target and the background clutters around this target.

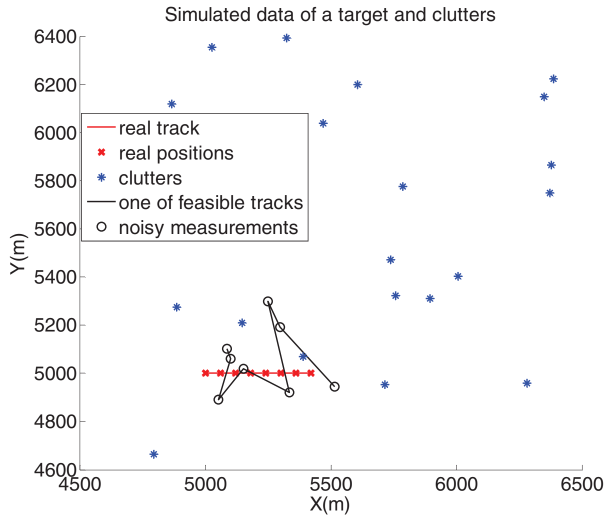

Fig. 9. One target and background clutters. The red line and red points mean the true positions of the target, the circles denote the noisy measurement positions of the target, the black line denotes a feasible track, and the blue points are the clutters.

Because track splitting and merging is a local concept, if two tracks or measurements are far away from each other, the track splitting and merging events cannot occur. So only some relatively small areas are concerned for our new method, not a large area. For example in the Fig.9, one of the four targets and its surrounding environment are considered, because targets are far away from each other. We set the area of interest as [4000 4000 7000 7000], larger than the area shown in the Fig.9. In once scan of the sonar, every measurement is attached to a unique label (scan index *k1*, the measurement index *k2*), i.e. the *k2*th measurement in the *k1*th scan.

As shown the table I, our new method creates 13 confirmed tracks after track splitting, and only one track is the true track (track3), others are all false tracks. There are many tracks created driving from track splitting, such as track2 and track3 split at the initial stage, track8 and track11 split at the medium-term stage, and the track1 and track4 split at the terminal stage. Only some tracks meet the rules of track merging. For example, track8 and track11 can merge into one track, but track5 and track7 cannot merge.

TABLE I
The list of tracks information

Index	Measurements information
1	(1.4),(2.7),(3.6),(4.2),(5.1)
2	(1.2),(2.9),(3.6),(4.2),(5.1)
3	(1.4),(2.9),(3.6),(4.2),(5.1)
4	(1.4),(2.7),(3.6),(4.2),(5.6)
5	(1.2),(2.9),(3.6),(4.2),(5.6)
6	(1.4),(2.9),(3.6),(4.2),(5.6)
7	(1.2),(2.8),(3.5),(5.2),(7.1)
8	(1.1),(3.3),(5.5),(6.3),(8.5)
9	(1.3),(3.3),(5.5),(6.3),(8.5)

10	(2.1),(3.5),(5.2),(7.1),(8.6)
11	(1.1),(3.4),(5.5),(6.3),(8.5)
12	(2.4),(3.5),(5.2),(7.1),(8.6)
13	(1.5),(2.3),(4.4),(5.9),(8.10)

If we analyze the confirmed tracks as shown the table I, tracks are divided into two groups, based on the similarity from each other, and the results are shown in the table II and III. All the tracks in the table II are formed at time 5, and they more or less contain the measurements from the true target. If compare all the tracks and analyze their positions, we find that the track2 and track3 are the nearest at the spatial position. Then it is reasonable to believe that these two tracks originate from the same target (track3 is the true track). By comparing and grouping, the track1 and track4 can merge into one track; track5 and track6 can merge. The table III lists the false tracks, and these tracks almost consist of the clutters. Among the false tracks, some tracks also meet the requirements of track merging rules, such as track8 and track9, track10 and track12. From the simulations and analyses above, we can obtain the true track by track splitting, even though there are a lot of false tracks. Then by track merging, we prune the false tracks, and decrease the false alarm. To some extent, track merging makes up for the disadvantages of track splitting. At last, the number of all tracks is 8. The results obtained from simulations and analyses provide strong evidences that our new method performs very well even in the presence of clutters and large measurement errors.

TABLE II

The true track (track3) and false tracks similar to the true track.

Index	Measurements information
1	(1.4),(2.7),(3.6),(4.2),(5.1)
2	(1.2),(2.9),(3.6),(4.2),(5.1)
3	(1.4),(2.9),(3.6),(4.2),(5.1)
4	(1.4),(2.7),(3.6),(4.2),(5.6)
5	(1.2),(2.9),(3.6),(4.2),(5.6)
6	(1.4),(2.9),(3.6),(4.2),(5.6)

TABLE III

False alarm (false tracks)

Index	Measurements information
7	(1.2),(2.8),(3.5),(5.2),(7.1)
8	(1.1),(3.3),(5.5),(6.3),(8.5)
9	(1.3),(3.3),(5.5),(6.3),(8.5)
10	(2.1),(3.5),(5.2),(7.1),(8.6)
11	(1.1),(3.4),(5.5),(6.3),(8.5)
12	(2.4),(3.5),(5.2),(7.1),(8.6)
13	(1.5),(2.3),(4.4),(5.9),(8.10)

VI. Conclusion

A significant improvement is made for the performance of tracking initiation for track splitting and merging events in a clutter environment when it utilizes all the measurements that pass a certain valid test. We propose a new method for the track initiation, based on modified logic-based method and MHT principle. In order to obtain the accurate tracks of targets and improve the detection probability of a track, based on MHT principle, we create a new feasible track for every measurement in the valid predicting region. Then we decrease the false tracks by track merging method. At last, our method can improve the detection probability and decrease the false alarm probability simultaneously. Its performance is illustrated by the simulations and analyses in which the method is tested in the underwater environment.

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