

Probabilistic Track Initiation Algorithm Using Radar Velocity Information in Heavy Clutter Environments

Gyujeong Lee
Seoul National University
Seoul, 08826
South Korea
regulation.lee@snu.ac.kr

Seungeui Lee
Seoul National University
Seoul, 08826
South Korea
dehlix@snu.ac.kr

Kwonsung Kim
Agency for Defense Development
Daejeon, 34186
South Korea
kims@add.re.kr

Nojun Kwak
Seoul National University
Seoul, 08826
South Korea
nojunk@snu.ac.kr

Abstract—In this paper, we propose a novel probabilistic track initiation algorithm using velocity information of measurements. The velocity information is converted to a probabilistic function and it is used to calculate the track score for track initiation. Moreover, we introduce the scheme of Non-Maximum Suppression (NMS) to determine candidate targets for tracking in terms of the track score. To verify the effectiveness of the proposed algorithm, we designed a simulator for target tracking. The simulation results show that the proposed algorithm has lower false track probability compared to conventional algorithms in heavy clutter environments.

I. INTRODUCTION

The track initiation is a very important stage in *multiple target tracking* (MTT) systems. Since a track initiation algorithm determines the initiation information for tracking targets, it directly influences the data association and tracking filter used [1]–[3]. Generally, conventional track initiation algorithms use mainly the geometrical relationships among measurements that have to be combined (e.g. distance, velocity, angle). The measurement combination is a sequence of measurements obtained from consecutive radar scans, which can determine the initialization of tracking. If geometrical relationships of measurement combinations meet a predetermined condition (e.g. relationship score exceeding a threshold), they are regarded as targets to track. The conventional algorithms operate effectively in normal clutter environments where the number of measurement combinations is rather small. However, since the number of these combinations can increase exponentially in heavy cluttered environments, the conventional algorithms have a high probability of initiating false tracks [4]. Since false tracks require unnecessary computational power for data association and running tracking filters, the performances of MTT systems in heavy cluttered environments can be degraded eventually [3]. To overcome this problem by reducing the false track probability, many studies have been proposed [5] [6].

Conventional track initiation algorithms are categorized as sequential methods and batch methods [4]. Sequential methods produce the combination of measurements sequentially using the measurements that exceed a threshold for each radar scan. If measurement combinations are maintained during a time window of an initiation process, these combinations are determined as targets to track. The M/N logic-based track initiation algorithm [7] is the most widely used in the radar

field. This algorithm is based on the sliding window process, where N is the number of scan and M is the detections out of N scans in the acceptance gate [7]. The sequential methods have low computational complexity. However, the probability of false track can be increased in heavy clutter environments, because the number of measurements that exceed a threshold can increase for each radar scan.

In the case of batch methods, every measurements from some period of radar scans are stored. Then, batch data of every possible measurement combinations are processed simultaneously. And if the measurement combination meets a threshold, these combinations are determined as tracking targets. Hough transform algorithm is one of the most popular batch methods, where Hough transform is used to detect lines or curves in images by transforming coordinate systems [8]. In a track initiation by Hough transform, all measurements (x, y) in a Cartesian coordinate system get transformed to values (ρ, θ) in a polar coordinate system. And it determines targets to track when measurements from a combination are collinear. It has reported that the batch methods are effective approaches in heavy clutter environments, because the statistics of the measurement combinations during several scan times are used to decide the initiation. However, this approach works effectively only after many scans [9].

While conventional methods utilize measurement information deterministically, score-based algorithms use probabilistic approaches. These state-estimation-based algorithms integrate track initiation, data association, and tracking filter stages into one. Typically, signal intensity, Doppler and position information are used to represent the state of measurements. *Kalman filter* and *probabilistic data association filter* (PDAF) are used for tracking and data association, respectively. Track scores are calculated based on error covariance matrix between measurement and prediction and the initiation of targets to track is determined according to these scores [10]. Since the probabilistic approach for targets as well as the estimation and prediction of the state are used, these algorithms are more accurate and suppress false track effectively [11]. However, they require more computational resources because all stages of MTT system are integrated. Thus, it is preferred to use separate algorithms for each stage, especially in heavy cluttered environments [9].

In this paper, we propose a novel probabilistic track initiation algorithm combining track scores based on velocity information. The proposed algorithm can be understood as a kind of combination of a score-based algorithm and a conventional algorithm. In order to take advantage of probabilistic approaches, we define the track score as a random variable that uses only the velocity information. Furthermore, we apply *the non-maximum suppression (NMS) method* to determine the target to track [12]. To verify the performance of the proposed algorithm, we design a track initiation simulator for analyzing track detection probability (P_D) and false track probability (P_F) [4].

II. TRACK INITIATION BASED ON VELOCITY INFORMATION

In this paper, the measurement combinations being evaluated is denoted as a “tentative track” and a tentative track that satisfies certain criteria is denoted as a “confirmed track”, which is passed to the data association and tracking filter stages. A “deleted track” is a tentative track that does not satisfy the criteria, which is deleted from memory.

In conventional track initiation algorithms, a velocity threshold is used as a basic condition for finding tentative tracks and can be represented as

$$v_{min} \leq v^i = \|r_{i+1} - r_i\| / t_s \leq v_{max}, \quad (1)$$

where, r_i is the target position vector at the i^{th} scan, t_s is the sampling period and v^i is the estimated velocity of measurement pairs at the i^{th} scan.

In logic-based methods, velocity information is used to predict the target position $r^i = r^{i-1} + v^{i-1}t_s + \frac{1}{2}t_s^2 \cdot a^{i-1}$ at i^{th} scan with acceleration information a^{i-1} , then the acceptance gate is set. Tentative tracks are expanded with measurements that meet the following condition

$$\|r_k^i - r^i\| < r_0 \quad (2)$$

where, r_k^i is the position of the k th measurement at i^{th} scan, r_0 is a threshold for acceptance gate.

In Hough transform based methods, initiating a target track in x - y plane is equivalent to searching the intersection points in the ρ - θ plane [4]. Angle threshold θ_0 is one of a condition to find the intersection points and can be expressed as

$$|\theta^{(i+1)} - \theta^{(i)}| \leq \theta_0. \quad (3)$$

A. Track Score Based On Velocity Information

To formulate the track score in terms of velocity information, we assume that the target velocity is approximately constant during the track initiation process if the sampling period is short enough. A constant target velocity means that the estimated velocity which is calculated by (1) would also be nearly constant. Based on the assumption, the level of variation of estimated velocity can be used as a criterion of track initiation. In other words, the track score is defined to increase the probability that a tentative track with smaller velocity variation becomes a confirmed track. The process which converts the velocity variation of a tentative track into a track score is described below.

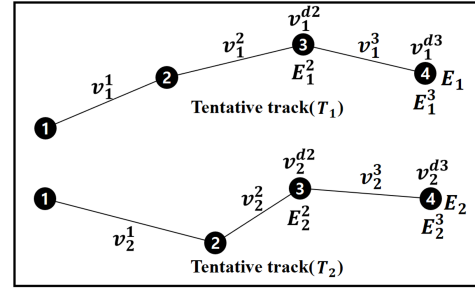


Figure 1. Concept of proposed track initiation algorithm in a two-target environment.

In the proposed algorithm, every measurement combination which satisfies the gating criterion of velocity and angle is assigned as a tentative track. The track score of each tentative track is calculated based on variations of velocity information probabilistically.

Let k be a tentative track index and v_k^i is a velocity information of k^{th} tentative track at i^{th} scan as in (1). As shown in Fig. 1, the velocity variation, $v_k^{d_i}$, between adjacent scan can be represented by Eq (4).

$$v_k^{d_i} = |v_k^{i-1} - v_k^i| \quad (4)$$

In order to assign a high track score to the tentative track that shows small velocity variation, the relative velocity variation Δv_k^i is defined as follows:

$$\Delta v_k^i = \left| \max_k (v_k^{d_i}) - v_k^{d_i} \right| \quad (5)$$

And, the likelihood that the i -th measurement of the tentative track, T_k^i , originates from a true target (H_1) is defined as:

$$P(T_k^i | H_1) = \frac{1}{Z} \exp(\Delta v_k^i) \quad (6)$$

where, Z is the partition function that is calculated as the sum of $\exp(\Delta v_k^i)$ for every k , and H_1 is hypothesis that the tentative track is originated from a true target.

Finally, the track score of a tentative track, $E(T_k)$ is defined by the sum of log-likelihoods of each scan as the following:

$$E(T_k) = \sum_{i=2}^{N-1} \log P(T_k^i | H_1). \quad (7)$$

Thus, the tentative track with smaller velocity variation corresponds to having higher track score. Since track scores are calculated by summing log-likelihoods for several scans, confirmed tracks can be determined based on accumulated information.

B. Non-Maximum Suppression(NMS)

The proposed algorithm is based on track scores, so we have to consider how to determine confirmed tracks among tentative tracks. So we introduce the NMS for determining confirmed tracks and reducing false track probability. The NMS is widely used for object detection tasks (especially edge detection techniques) in the computer vision domain [12]. The

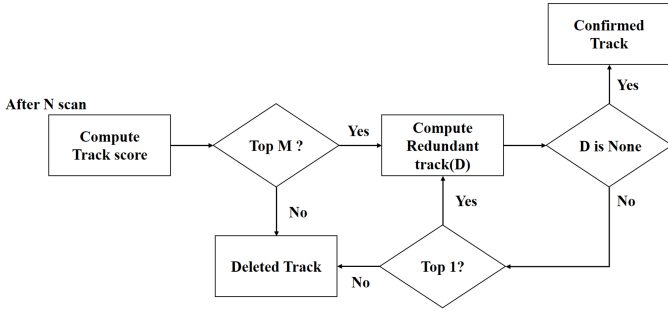


Figure 2. Block diagram of the proposed track initiation algorithm with the NMS scheme.

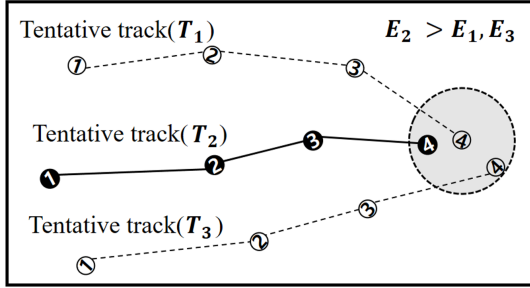


Figure 3. NMS approach. The track with solid line has maximum track score. Due to T_2 , the tracks in dashed line are assigned as deleted tracks.

conventional process of NMS in computer vision is as follows: First, it sorts all detection boxes by their scores. Then, the detection boxes with a significant overlap are suppressed except the one with the maximum score. Inspired by this process, we apply the analogous process as used in object detection tasks. Our process of NMS in the proposed track initiation algorithm is as follows. First, to reduce processing time, TOP- M tentative tracks based on the track scores are selected as the NMS input, where M is the average number of clutter points per scan. Next, adjacent tentative tracks in distance satisfying (8) are assigned as a "redundant track", R_k . The distance between tentative tracks is calculated based on the N_{th} measurement of each tracks where N is the final scan of the initiation process.

$$\|T_k^N - T_m^N\| \leq \delta_0, \quad m = 1, 2, \dots, K \quad (8)$$

where, K is the number of tentative tracks and δ_0 is the NMS threshold.

As shown in (9), redundant tracks are assigned as deleted track, D_k except the one with the highest track score. The NMS is iterated until there is no more redundant track. After the NMS is done, remaining tentative tracks are assigned as confirmed tracks.

$$T_k = \begin{cases} T_k & \text{if } T_k = \underset{T_k \in R_k}{\operatorname{argmax}} E(T_k) \\ D_k & \text{otherwise} \end{cases} \quad (9)$$

The block diagram of the proposed algorithm is shown in Fig.2. Fig.3 shows an example of the NMS. Suppose there are three tentative tracks in observation region. The number in circle

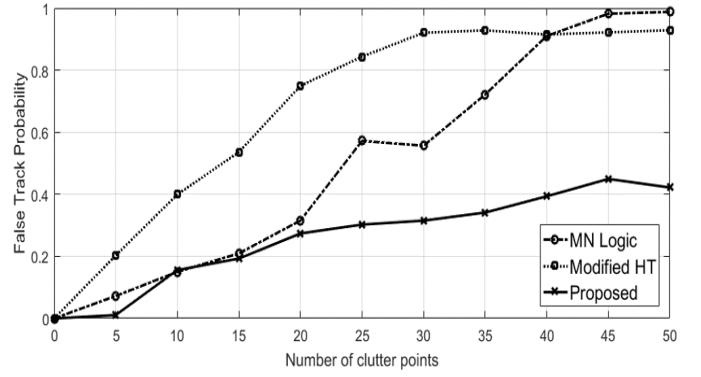


Figure 4. False track probability (P_F) in heavy clutter environment. M/N logic(the dotted line), modified Hough transform(the dashed line), and proposed algorithm(the solid line)

indicates the radar scan time of measurement. For the tentative track T_1 , gray circle indicates a threshold, so its redundant tracks are tentative track T_1 , T_2 and T_3 . Thus, only T_2 with the maximum track score survives and T_1 and T_3 are assigned as deleted tracks.

Through the NMS process, we can remove tentative tracks that are assigned to the same measurement and tentative tracks that are approximately at the same position. However, finding optimal threshold is an open question, so this will be investigated in subsequent studies.

III. SIMULATION AND ANALYSIS

We design our simulations in Matlab R2016b and 1,000 Monte-Carlo trials have been carried out to evaluate the performances. Five true target trajectories with different initial positions are used. Trajectories are generated with the same constant velocity $v = 350\text{m/s}$ and heading $\theta = -50^\circ$ in xy -plane. We follow $N = 4$ -scan initiation process and a sampling period is set as $t_s = 1\text{s}$. The number of clutter points (N_c) in each scan is assumed to have Poisson distribution and the location of these clutter points is assumed to have uniform distribution in the observation region 4km^2 following [1]. The parameters for the track initiation are $v_{min} = 40\text{m/s}$, $v_{max} = 700\text{m/s}$, $r_0 = 80\text{m}$ and $\theta_0 = 15^\circ$. Two baselines which are the M/N logic based method and the modified Hough transform based method are used to verify the performance of the proposed algorithm. Track detection probability (P_D) and false track probability (P_F) are defined as follows [4]:

$$P_D = \frac{\text{Number of correct track formed}}{\text{Number of true track present}} \quad (10)$$

$$P_F = \frac{\text{Number of false track formed}}{\text{Number of average clutter point}}. \quad (11)$$

Fig. 4 shows that the P_F against various numbers of the clutter points, N_c . To simulate a heavy clutter environment, we set the clutter density up to $1.25 \times 10^{-5}/\text{m}^2$. The measurement error with standard deviations of $\sigma_r = 10\text{m}$ (range) and $\sigma_{az} = 3.5 \times 10^{-3}$ rad (azimuth angle) is applied. The proposed

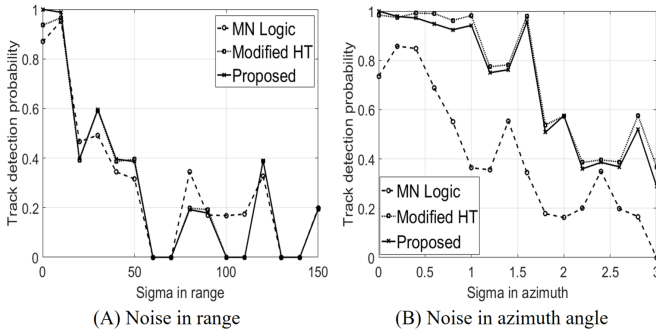


Figure 5. Track detection probability with range noise (A) and azimuth noise (B). The legends of the plots are the same as Fig.4.

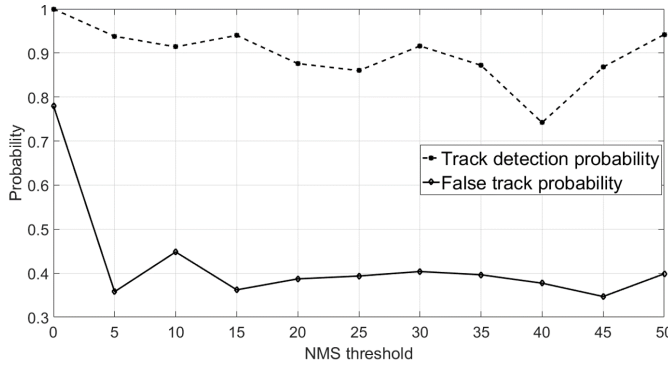


Figure 6. Performance evaluation on NMS threshold. Track detection probability(the dashed line) and false track probability(the solid line).

algorithm shows a lower P_F than the conventional algorithms in the heavy clutter environment. Especially, the PF did not increase significantly despite the increased number of clutter points. This can be seen as a result of iterative NMS process to adjacent tentative tracks. Fig. 5 shows the P_D on measurement errors. We set the clutter point $N_c = 20$. The proposed algorithm shows similar performance to the conventional track initiation algorithms in range and azimuth angle error. Because the proposed algorithm is based on velocity information which is sensitive to the measurement error, the detection probability can be enhanced by introducing additional information such as signal intensity or Doppler information. The track initiation performances of the proposed algorithm is shown in Fig. 6 in terms of diverse NMS threshold. We set the expected number of clutter points to be $N_c = 40$, and the measurement error to be $\sigma_r = 15\text{m}$, $\sigma_{az} = 3.5 \times 10^{-3}$ respectively. It can be seen that P_F decreases as the NMS threshold increases. However, P_D also decreases slightly as the threshold increases. It means that false tracks with higher track score than the true target can appear in redundant tracks due to the number of redundant tracks grows. Therefore, the NMS threshold should be determined in consideration of the balance between P_D and P_F .

IV. CONCLUSION

In this paper, we proposed the new probabilistic track initiation algorithm in heavy clutter environments. The proposed algorithm defines the track score based solely on the velocity information without the state-estimation. The result of simulation showed that the proposed algorithm has up to 57% performance improvement on false track probability compared to conventional algorithms in heavy clutter environments. In addition, the use of the NMS scheme provides the ability to keep low false track probability even though the number of clutter points increases. However, the proposed algorithm has similar track detection probability compare to conventional algorithms on the measurement error. This means that the proposed algorithm can be applied effectively in heavy clutter environments but it is sensitive to measurement error due to utilizing only velocity information.

As a future work for enhancing the robustness of the proposed algorithm to measurement error, additional state information (e.g. signal-to-noise ratio, Doppler information) would be studied. Furthermore, various simulation environments (e.g. clutter statistical model) would be researched to verify the effectiveness of the proposed algorithm for practicality.

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