# TWO-STEP DETECTION ALGORITHM FOR FLUCTUATING WEAK TARGET BASED ON DYNAMIC PROGRAMMING

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***ABSTRACT***

*Multi-frame data are processed simultaneously in Track-before-Detect (TBD) algorithm, which is an effective means to improve signal-to-noise ratio. However, some key factors, such as fluctuation loss and multi-frame joint threshold, are neglected when detecting weak target, which leading to detection performance loss inevitably. In order to address the above problems, a novel dynamic programming-TBD (DP-TBD) algorithm based on two-step thresholds is proposed in this paper. Firstly, the multi-frame accumulation amplitude for the observation scene is recalculated based on fluctuation loss analysis and measurement updating, as a result, the accumulation amplitude is closer to the real situation. Then, the first level threshold based on multi-frame data is achieved through the proposed threshold setting method, which avoiding the disadvantage of CFAR algorithm in which the false alarm trajectory cannot be separated effectively from the real target trajectory. Finally, the quantity for false alarm trajectory is decreased further by setting the second level thresholds, which depending on the distribution characteristics of the residual false alarm trajectories. The proposed algorithm takes full advantage of multi-frame joint detection for fluctuating weak targets, which giving consideration to both detection performance and false alarm performance. Simulation results show the effectiveness of the proposed algorithm.*

***KEYWORDS****: Fluctuating weak target; track-before-detect; dynamic programming; threshold; trajectory processing*

## 1.0 INTRODUCTION

With the rapid development of potential threats, e.g. ballistic missiles, stealth aircraft, etc, which show common features of small radar cross section (RCS) and fluctuating characteristic with visual angle, surveillance radar systems are confront with a challenging task due to the low signal-to-noise-ratio (SNR) characteristics.

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An efficient way to enhance the SNR of fluctuating weak target is to employ multi-frame energy accumulation strategy, that is to exchange time for SNR improvement. Presently, many multi-frame detection algorithms have been demonstrated by domestic and overseas scholars. Constant false alarm rate (CFAR) algorithm (Jin, Zhou & Yin, 2016; Rui, Wei & Nguyen, 2016) are capable of monitoring targets with low false alarm rate, which is reasonable in single-frame processing. However, it shows poor performance when handling multi-frame data since the corresponding threshold could simply eliminate the false alarm trajectories caused by noise rather than those caused by the combination of target and noise. Two-step threshold detection TBD algorithm (Yi, Kong & Yang, 2013; Cao, Zhang & Xiang, 2013) is developed to reduce the amount of computation, but high-level primary threshold may cause incomplete target path for low SNR target, particularly for fluctuating weak target. Conversely, low-level primary threshold also lost its significance because the false alarm trajectories caused by noise cannot be removed effectively. Trajectory processing TBD algorithm, which takes the difference between target trajectory and false alarm trajectory into account, is a valid way to reduce false alarm rate. For these false alarm trajectories composed of target and strong noise, which are generally formed by target energy diffusion in the track-backtracking process, can be eliminated by trajectory overlapping method (Johnston & Krishnamurthy, 2002; Yi, Kong & Yang, 2009). Another set of false alarm trajectories, which are totally composed of strong noise, can be judged as false alarm trajectories by counting the yaw angle difference between adjacent frames (Liu, Wang & Qiu, 2011; Grossi, Lops & Venturino, 2013; Song, Gao & Tian, 2006), this is because almost no correlation exist within two neighboring frames for these trajectories. The above mentioned multi-frame detection methods, however, are still ineffective if adjacent target interference exist in the scene. Therefore, both false alarm trajectory and adjacent target interference need to be considered simultaneously in the follow-up study.

Theoretically, the ideal target RCS is acquired through counting a large number of multi-directional measured data in practical application, so it is almost impossible to get the real value for fluctuating target (Hu, Gao & Fang, 2015). For convenience, the target fluctuation model is defined as four types, including Swerling I,II,III and IV (Hyeongyong, Dongweon & Gao, 2018; Bakry, 2018). In this way, the target SNR can be analyzed quantitatively according to its fluctuation model. In order to avoid SNR loss caused by traditional detection algorithm (Bi, Du & Zhang, 2015; Li, Wang & Yu, 2017; Long, Liang & Liu, 2019), a multi-frame joint DP-TBD detection algorithm is proposed in this paper, where the fluctuation model is set to Swerling I and matches well with most of the fluctuating weak targets for surveillance radars. On one hand, by setting the first level threshold based on multi-frame cumulative amplitude, an overwhelming majority of the false alarm trajectories caused by noises are removed while the real target trajectory are preserved. On the other hand, the remaining false alarm trajectories are further eliminated by means of the second level threshold, which depending on the trajectory overlapping number and multi-frame direction statistics. Simulations results show that the proposed algorithm is superior in both detecting and tracking performance.

This following paper is outlined as follows. Fluctuation loss analysis is theoretically described in section 2. In section 3, the first level threshold setting method is analysed in detail. The second level threshold setting method is depicted in section 4. Simulation results are shown in section 5 to verify the effectiveness of the proposed algorithm. A brief conclusion of this paper is given in section 6.

## 2.0 FLUCTUATION LOSS ANALYSIS

Most of the existing TBD algorithms for weak target detection assume Swerling V as the fluctuation model. However, target RCS changes with observation angle in energy accumulation process, which lead to the detection performance degradation.

Target fluctuation characteristic is generally divided into four categories (Swerling I-IV), among which Swerling I and Swerling III belong to slow fluctuation, while Swerling II and Swerling IV belong to fast fluctuation. If the target fluctuation model is in accordance with Swerling II and Swerling IV, coherent accumulation no longer applies because different pulse phases cannot maintain relevant. Considering most of the concerned weak targets obey Swerling I model, Figure 1 reveals the relationship between detection probability and SNR under Swerling I model and Swerling V model respectively, where the false alarm rata is set to 1e-9 and pulse accumulation number is selected as 10.

Figure 2 takes Swerling I model as an example and shows the extra SNR needed to obtain a certain detection probability. Thus, target detection probability can be achieved from Figure 1 according to the given false alarm rate and SNR, and the corresponding fluctuating loss can be calculated from Figure 2. If fluctuating loss is leave out of account, the adaptive threshold will make the detection threshold increased because the observation value is larger compared with actual value, which resulting in detection loss.

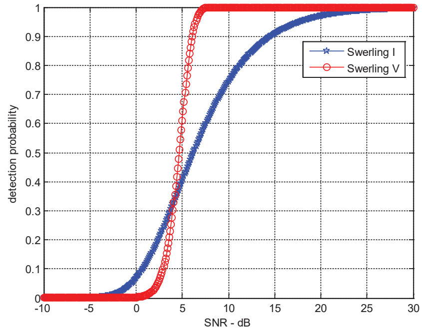



**Figure 1** Relationship between SNR and detection probability

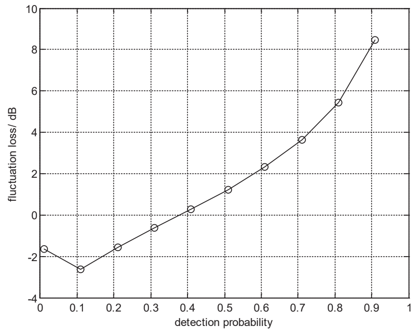



**Figure 2** Relationship between fluctuation loss and detection probability

## 3.0 FIRST LEVEL THRESHOLD SETTING METHOD BASED ON MULTI-FRAME DATA

With regard to traditional two-step threshold detection TBD algorithm (Yi, Kong & Yang, 2013), high-level primary threshold may cause incomplete target path for weak target, while low-level primary threshold have no effect because the false alarm trajectories caused by noise cannot be removed effectively. Therefore, the first level is meaningless as the target SNR is an unknown value. In addition, the constant false alarm criterion is generally adopted in the second level threshold setting process, in which the trajectory accumulation amplitude composed of target and strong noise is close to those totally composed of target, so it is difficult for CFAR algorithms to remove the former false alarm trajectories. In this section, a multi-frame threshold selection method for DP-TBD is discussed, and the principle of this algorithm is as follows:-

Assume that there are targets in the observation scene, in which the target motion state in frame can be expressed as $\boldsymbol{x}_k^m = [p_{x,k}^m, v_{x,k}^m, p_{y,k}^m, v_{y,k}^m]^T$, where $m = 1, \cdots, T$, $p_{x,k}^m$, $p_{y,k}^m$, $v_{x,k}^m$ and $v_{y,k}^m$ stand for positions and velocities along X-axis and Y-axis. Multi-target motion equation is defined as in Equations (1) and (2) as follow:-

$$\boldsymbol{x}_k^m = \boldsymbol{F}\boldsymbol{x}_{k-1}^m \tag{1}$$

where

$$\boldsymbol{F} = \begin{bmatrix} \boldsymbol{F}_s & 0 \\ 0 & \boldsymbol{F}_s \end{bmatrix} \qquad \boldsymbol{F}_s = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \tag{2}$$

where $a$ represents random number in the range of 0 and 1.

In this way, $T_1$ is an adaptive threshold, which indicates that if the max accumulative amplitude *Max* is a minor value, that is the average SNR per frame is less than 6dB, $T_1$ is set to 0.9 *Max* which decreasing the false alarm trajectories caused by noise efficiently. Conversely, if *Max* is a large value, that is, the amplitude of target is quite different from noise, then $T_1$ is broadened to $(1 - 10^{-13/20})$ *Max = 0.78 Max*. Thus, the false trajectories caused by noise are removed, besides, the false dismissal problem produced by fluctuation loss also declined. Figure 3 shows the multi-frame data association diagram, in which the observation data within each frame is composed of multi-target and noise. Note that the main purpose for first level threshold setting process is to remove the trajectories mainly caused by noise, it is more applicable for the proposed adaptive threshold to eliminate those trajectories compared with constant false alarm threshold. For the mix trajectories composed of target and noise, section 4 will give further elimination strategy by employing the second level threshold setting method.

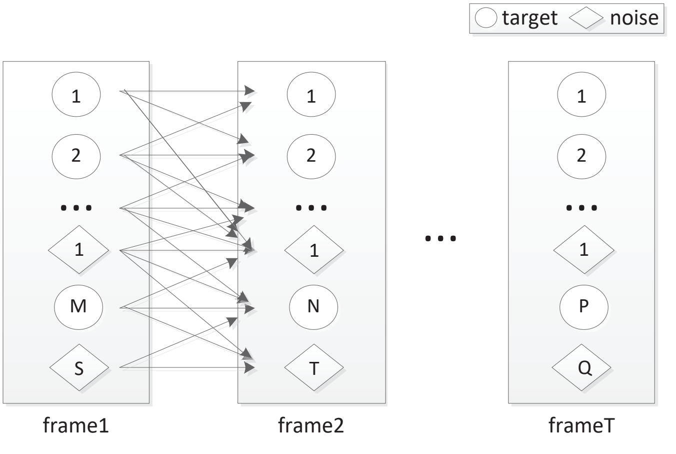



**Figure 3** Multi-frame data association diagram

## 4.0 SECOND LEVEL THRESHOLD SETTING METHOD BASED ON MEASUREMENT UPDATING

Compared with trajectory overlapping method and direction statistic method, second level threshold setting method based on measurement updating does not search for the candidate trajectory directly, instead, the corresponding trajectory amplitude in each frame is updated preferentially (Li, Huang & Lin, 2016). Here, zero amplitude assignment operation is abandoned, which avoiding the measurement missing problem when multi-target trajectories possess overlaps. Moreover, by setting appropriate thresholds for yaw angle difference between adjacent frames and the accumulative yaw angle difference among multi-frame independently, the mixed trajectories composed of target and noise can be eliminated steadily, which providing an effective solution to extract the actual target trajectory. The main steps of second level threshold setting method can be summarized as follows:-

Step 1: Constituting candidate trajectory set using track-backtracking operation.
Carry out multi-frame track-backtracking operation according to the final frame observation and target motion model, and put the trajectories whose accumulative amplitude is greater than into candidate trajectory set.

Step 2: Search and save the target trajectory.
Seeking for the max accumulative amplitude in the candidate trajectory set, which is considered belonging to the target trajectory.

Step 3: Updating unit amplitude of the target trajectory.
Calculating the average accumulative amplitude achieved in step 2 and updating the corresponding unit amplitude in each frame. That is, subtracting the average accumulative amplitude from each unit amplitude in target trajectory, where the unit amplitude is set to 0 if this updated value is negative. Meanwhile, the same operation is carried out for those trajectories in which the overlap number is higher than ($L$, $L = T/2$, and $T$ stands for the frame number).

Step 4: Updating the unit amplitude of the trajectory composed of strong noise.
Counting the yaw angle difference angle($v_i$ -$v_i$-1) (1<i< $T$ + 1) between adjacent frames, where $v_i$ is the trajectory direction between the *ith* frame and ($i$–1)*th* frame. For candidate trajectories, if more than *round*($T$ / 4) frame data whose

yaw angle difference exceed $T_{angle1}$ ($T_{angle1}$ is assigned as pi/4 in the following simulation), those trajectories will be considered as false alarm trajectories, where *round* represents rounding operation. Then the unit amplitude updating operation in section 3 is carried out for those trajectories. Otherwise, calculating the accumulative angle difference in the residual candidate trajectory set, if this value exceeds $T_{angle2}$ ($T_{angle2}$ is assigned as $pi*T/6$ in the following simulation), the corresponding trajectory is still regarded as false alarm ones, in which the unit amplitude will be updated using the same operation in section 3.

Step 5: Judging whether the proposed algorithm meet the terminate conditions. Continue searching for the trajectory which processing the max accumulative amplitude. If this value is less than  , stop iteration and output the target trajectory; Otherwise, turn to step 2 and repeat the searching process for target trajectories. Figure 4 demonstrates the flow chart of two-step detection algorithm based on dynamic programming.

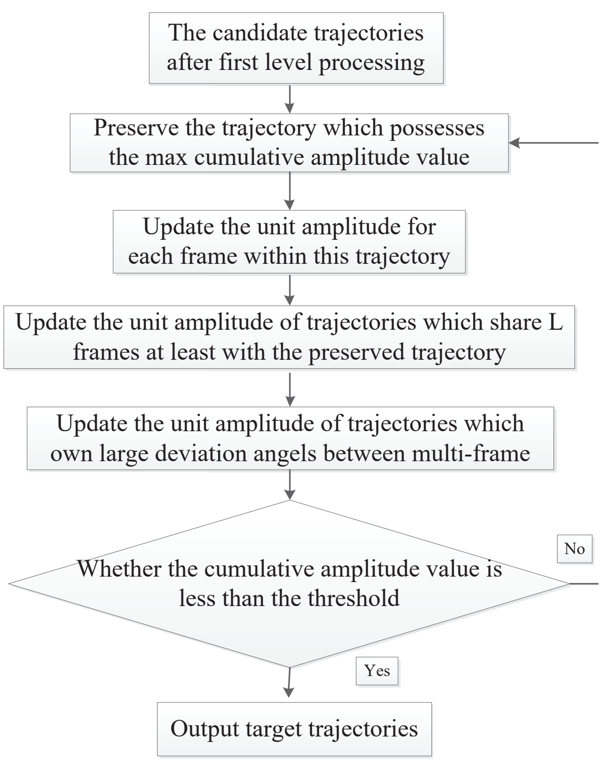


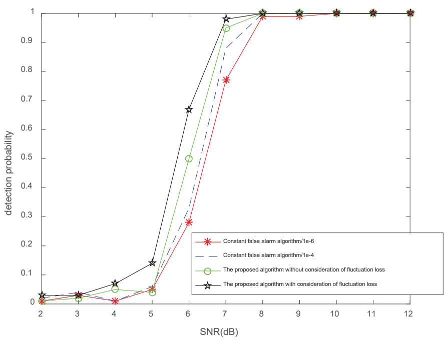

**Figure 4** Flow chart of two-step detection algorithm based on dynamic programming

## 5.0 SIMULATION RESULTS

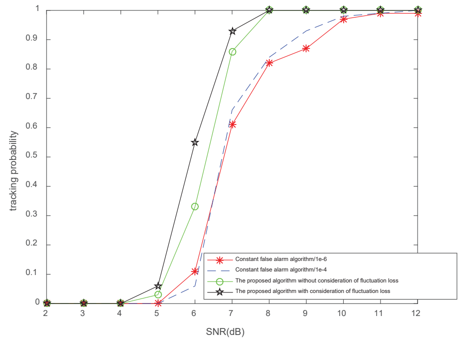
In this section, simulations are performed to illustrate the performance of the proposed strategy. Let target 1 and target 2 move crosswise with uniform speeds. The initial states of these two targets are [10,2.5,10,2.5] and [40,-2.5,10,2.5], where the four items stand for positions and velocities along X-axis and Y-axis in turn. For the following simulations, assume noise obeys normal white Gaussian distribution, the total accumulative frame number is set to 10, SNR is selected as 6dB, and Monte Carlo simulation time is 150. The relationship between SNR and amplitude satisfying $SNR$ = 101g($A^2$ / $\sigma^2$, where $A$ and $\sigma$ indicate the target amplitude and standard deviation of noise, respectively.

Here, successful detection is defined that the accumulative multi-frame amplitude exceeds detection threshold, meanwhile, the deviation of target position at last frame is less than two resolution units. While successful tracking is defined that the accumulative multi-frame amplitude exceeds detection threshold, and the deviation of target position within each frame is less than two resolution units.

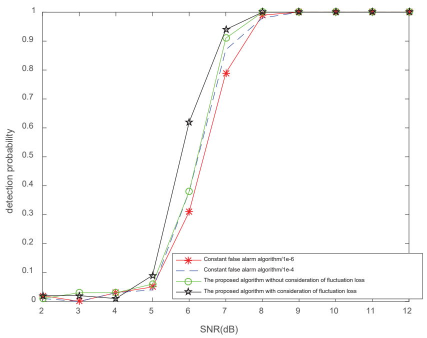
Figure 5 shows the detection probability and tracking probability using different algorithms. Obviously, compared with CFAR algorithm (The false alarm rate is selected as $1e^{-6}$ and $1e^{-4}$, respectively) and the detection algorithm in which fluctuating loss is neglected, the detection probability and tracking probability are improved by employing the proposed algorithm through amplitude updating strategy. Meanwhile, the missing detection problem of updating strategy in traditional DP-TBD algorithm is avoided, in which all of the unit amplitudes are set to 0.




(a)Detection probability of target 1




(b)Tracking probability of target 1



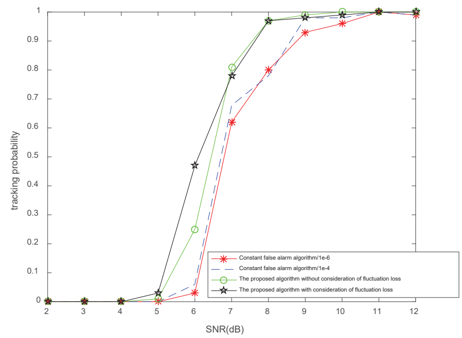
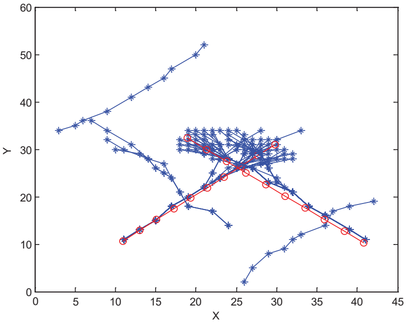



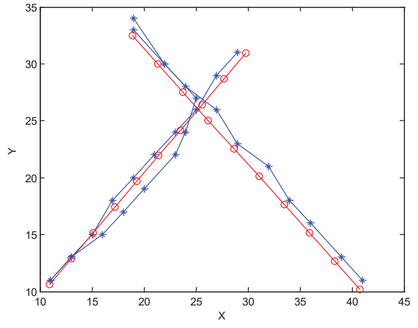

**Figure 5** Detection and tracking probability curves using different algorithms

In the above simulations, the proposed algorithm shows excellent detection performance compared with other algorithms, next false alarm performance is accomplished in detail. Considering the candidate trajectory set is almost totally composed of the mixed trajectories rather than noise trajectories by means of first level threshold setting method, the residual false alarm trajectories are eliminated effectively using second level threshold setting method. In this way, both detection probability and false alarm probability could achieve better performance.

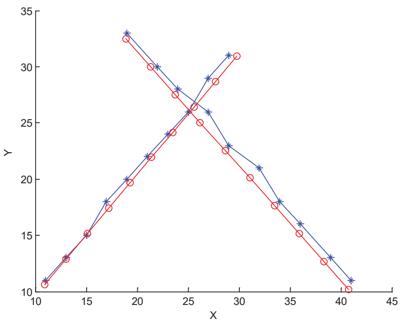
Figure 6(a) shows the candidate target trajectories among 10 frame using track-backtracking operation by employing first level threshold method. Figure 6(b) and Figure 6(c) compare the processing results by applying trajectory overlapping combined with direction histogram statistics method and second level threshold processing method respectively, in which the red curves stand for the real target trajectories, while the blue curves stand for the processed target trajectories. Clearly, the proposed strategy could eliminate false alarm intersecting trajectory efficiently and extract the criss-cross target trajectories precisely. This is due to second level threshold setting process based on length threshold and angle threshold could dig into the characteristics of false alarm intersecting trajectory sufficiently for multi-frame joint detection.



(a)Candidate trajectories using first level processing method



(b)Trajectories using trajectory overlapping and direction histogram statistics method



(c)Trajectory using second level threshold processing method

**Figure 6** Trajectory processing results using different algorithms

## 6.0 CONCLUSION

In view of the existing problems in multi-frame joint processing, a novel DP-TBD algorithm based on two-step thresholds is proposed for fluctuating weak target detection, in which fluctuation loss, multi-frame joint threshold and trajectory processing are taken into account simultaneously. By taking full advantage of multi-frame joint detection strategy, the false alarm trajectories can be removed effectively. Compared with recent works, simulation results indicate that the proposed algorithm could achieve better performance when handling multi-frame processing.

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