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Journal of Harbin Institute of Technology (New Series), Vol. 18, No. 1, 2011

The TBD method for dim targets based on multi-level crossover and matching operator

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Abstract: In order to improve the tracking performance in this paper following TBD(Track before Detection) framework multi-level crossover and matching operator is presented. In data association stage the greedy principle is adopted to handle time complexity in DPA and at the same time crossover mathing operator is given to construct candidate trajectory. In addition the corresponding strategy is introduced in preprocessing and post-processing to remove clutter and suppress false alarm rate. By the experimental comparison and analysis it can be found that the method is more perfer to strengthen the tracking performance of targets with SNR < 2.0 dB.

Key words: track before detection; high order correlation filter; crossover operator; dynamic programming

CLC number: TP393.4 **Document code**: A **Article ID**: 1005-9113(2011)01-0057-05

For the detection of dim point targets (imaged only one pixel) in heavy clutter the TBD scheme has been the main research ideas. Over the years, several classical target detection techniques have been proposed in the literatures which used different schemes such as 3D spatial-temporal filtering[1], sequential hypothesis testing[2] and joint probabilistic data association (JPDA) in conjunction with a Kalman state estimator[3], all of which have been used in different situations. In Ref. [4] DPA is presented to substitute the infeasible exhaustive search over all possible trajectories in 3S. It avoids the use of a prethresholding filter, preserving all the weak signal information of the raw sensor data set. However, for the image sequence with heavy clutter it will soon have insufficient memory and great time overhead. In additional, for all of the above mentioned schemes certain assumptions about the target signature and the background clutter are made in order to reduce the computational requirement. Once lack of the priori information about the statistics of signals, clutter and noise, the performance of these techniques may decline quickly and it will not give superior results.

Liu had presented an effective clutter restrain method namely' high order correlation algorithm'[5]. He investigated the consecutive temporal and spatial dependencies of the points on a track to discriminate them from background clutter without creating the dynamical equation. Experiments showed that the clutter rejection rate will be 98% when the clutter intensity below 0.8%. When it is over 1.1% much false alarms will be created. The method sacrifices system time and extend the target trace by associating image constantly to complete detection.

Some national researchers presented new algorithms which are based on Top-hat morphology operator combined with other methods[6-7]. However, they are still in the frame of DBT. The selection of target depends on threshold and the target will have some spread in scale else they cannot be extracted by structure element so that it can not deal with point targets.

A multi-level crossover and matching operator was proposed in this paper. The candidate trajectories segments were created based on greedy principle and then the crossover matching operator was used to associate these segments into a trajectory. By matching the lower-level segment (called successor) with the proper parent according to the scoring principle the best individual was kept. By this way on one hand wrong data associations were reduced as much as possible and the other hand time complexity was confined to an acceptable degree.

1 Algorithm Discription

1.1 Preprocessing

Preprocessing was completed by using time and spatial filter. Firstly spatial filter was carried out by kernel function smoothing method and then time frequency filter was completed by projected along time axis to remove part of noise and clutter.

In all of the single variable kernel function, Fuller kernel function has the strongest ability to estimate the

Received 2009-07-13.

Sponsored by the Young Talent Program of Fujian Province (Grant No. 2007F3097).

background, and the Uniform kernel function can preserve most target information[8]. If the background prediction is accomplished by any one of them, it will not achieve the purpose. Yet if they are combined together we will get a satisfied result. In this paper which is named as compound kernel function.

The residual image sequence after compound kernel function filtering is marked by Res_{frame}. From analysis of the target properties it can be found that the target has the non-still property. The target will have relatively higher intensity while accumulating the time sequence for the same pixel in each image. The new projective sequence is:

$$\max\_project_{frame}(i,j) = \begin{cases} Res_{frame}(i,j); & \text{if } Res_{frame}(i,j) \geqslant \frac{1}{W}\sum_{\mathrm{frame}=1}^{N}(Res_{frame}(i,j)),\ Res_{frame}(i,j) > 0 \\ 0; & \text{else} \end{cases} \quad (1)$$

Therein, $\max\_project_{frame}$ is the image after projection; w is the sum of pixels with positive intensity while projected along the time axis. After preprocessing the noise removal ratio is up to 80% generally.

The clutter rejection ratio is defined as $1 - \frac{\text{the number of pixels in processed image}}{\text{the number of pixels in original image}} \times 100\%$.

1.2 High Order Correlation

Push sequence $\max\_project_{frame}$, $frame = 1.\ N$ into high order correlation filter and test the relativity of each pixel to get rid of noise.

Backward correlation process:

$$R^{order}(node,t_k) = \Big[R^{order-1}(node,t_k) \times \sum_{area_1 \equiv [-|v|,|v|]^2} R^{order-1}(node + area_1, t_{k+1}) \times \sum_{area_2 \equiv [-|v|,|v|]^2} R^{order-1}(node + area_1 + area_2, t_{k+2})\Big],$$
$$k = 1,2,\cdots N-2,\ order = \lfloor \frac{N-k}{2} \rfloor \quad (2)$$

$Order = 1$,

$$R(node,t_k) = binary\_\ image(node,t_k) \times \sum_{area_1 \equiv [-|v|,|v|]^2} binary\_\ image(node + area_1, t_{k+1}) \times \sum_{area_2 \equiv [-|v|,|v|]^2} binary\_\ image(node + area_1 + area_2, t_{k+2})\Big]$$

$$R^{order}(node,t_k) = \Big[R^{order-1}(node,t_k) \times \sum_{area_1 \equiv [-|v|,|v|]^2} R^{order-1}(node + area_1, t_{k-1}) \times \sum_{area_2 \equiv [-|v|,|v|]^2} R^{order-1}(node + area_1 + area_2,\ t_{k-2})\Big],$$
$$k = 3,\cdots N,\ order = \lfloor \frac{k-1}{2} \rfloor \quad (3)$$

which indicates the correlations between three consecutive frames; where v is the maximum target speed range; *order* is the order of the recursion, and *binary_ image* indicates the image after segmentation. If $R^{order}(node, t_k) \geqslant 1$, it means that originated from node there are $2order + 1$ consecutive frames which is regarded as extended node, else the node is abandoned. Using Eqs. (2) and (3) will get two groups filtered sequence with length of $N-2$.

1.3 Multi-level Crossover and Matching Operator

After higher order filtering process, the clutter rejection ratio is up to 90%. To resolve the time complexity of DPA in the following process we propose the multi-level crossover matching operator. In addition, we carry out data association in one direction different with the 8 directions in Ref. [9] and the time can be reduced further more.

1.3.1 Data association

From every point in every frame we carry out data association and construct trajectory segments, but different from the DPA, each step a best state will be selected to form segment based on Greedy Principle.

For the filtered sequence named as co-correlation-sequence the following steps are carried out:

- *Initial*: $i = 1$, *take every pixel in* $frame_i$ *as start point (marked by head)*,

Let $scoring = gray_{head}$, $mark = 0$ and create a multi-level list named *list* and merge the head:

$List = List \cup head$

- Take out the tail of *list* to search the candidate node in its adjacent area.

While a satisfied node is found in its adjacent area or $mark = 0$, test whether or not the nodes in its adjacent area to meet with the following conditions:

$$x = \arg_{node \in area} \max(gray_{node})\ \&mark = 1$$

Namely the node will have the property of local gray maximum and continuity:

$$R(node_x, frame) = binary\_\ image(node_x, frame) \times \sum_{area_1 \equiv [-|v|,|v|]^2} binary\_\ image(node_x + area_1, frame + 1) \times \sum_{area_2 \equiv [-|v|,|v|]^2} binary\_\ image(node_x + area_1 + area_2, frame + 2)\Big] \geqslant 1 \quad (4)$$

In addition the curvature limitation will be included to constraint the shape of trajectory. For a node in various positions different measures will be taken (as shown in Fig. 1).

a) $i = 2$, for the first three point segment we will consider the angle θ_{12} between node ① and node ② and regard it as a constraint to test the continuity of node ③ which will satisfy the condition

$$|\theta_{12} - \theta_{23}| \leqslant 30° \quad (5)$$

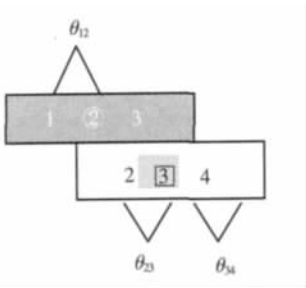

Fig. 1 The curvature of a node in different position

b) $i \geqslant 3$, while choosing the proper node ③ , for there are two three point segments 1-2-3 and 2-3-4, the following conditons will be considered:

$$|\theta_{12} - \theta_{23}| \leqslant 30° \ \& \ |\theta_{23} - \theta_{34}| \leqslant 30°. \quad (6)$$

c) For the node satisfied the above conditions,

$$mark = 1; List = List \cup node;$$
$$\theta_{12} = \theta_{23}$$
$$scoring = scoring + gray_{node};$$

$$\text{Else} \quad \begin{matrix} mark = 0 \\ gray_{node} = 0 \end{matrix}$$

• For $i = 1, \cdots N-2$, repeat step 2 and create candidate segments (lists) starting from every pixel in $frame_i$ and the shortest segment is constituted of frame indexed by $N-2$, $N-1$, and N.

1.3.2 Crossover and matching operator

Firstly, some definition will be introduced:

• Parent: the start node of every list is called parent;

• Direct successor: the list linked to the parent is called direct successor;

• Crossover successor: we call the list composed of frame indexed by $N-2$, $N-1$, and N is crossover successor;

Secondly, to enhance the performance of detection this section we trace back from bottom to top and carry out matching process step by step. It is executed as follows:

• $K = 4$;

• Calculate the scores of the list (length of K) composed of the direct successor with its parent marked by $scoring_{\text{old}}$;

• Calculate the scores of the list composed of the crossover successor with the parent marked by $scoring_{\text{new}}$;

• According to scoring principle if $Scoring_{\text{old}} < Scoring_{\text{new}}$ then match the crossover successor with the parent else keep the original list unchanged;

• Take the list after matching as new crossover successor;

• $K = K + 1$;

• If $K \leqslant N$ go to Step 2 else end.

1.4 Post Processing

After last stage we have got the candidate trajectories composed of time sequence indexed by 1 to N. However, there is also amount of clutter trajectories which consist of False Alarm disturbing target recognition. In this section we will adopt multi-information association to remove clutter as many as possible.

1) smoothing constraint

In order to assure the smoothness of the final trajectory, the following steps will be executed:

• one by one calculate the curvature of each trajectory every three point;

• Remove the trajectory with curvature not meeting with the max curvature constraint.

2) intensity constraint

The target's trajectory usually has a rather steady gray intensity, but not for the random noise or clutter segments. By this intensity constraint most noise or clutter trajectories will be removed.

• identify the min gray level and max gray level of trajectory j: $\max(gray_j)$, $\min(gray_j)$

• get the difference of the mentioned gray level

$$difference_j = \max(gray_j) - \min(gray_j)$$

• If $difference_j > 0.5$ then take it as clutter to remove. 0.5 is a prior value.

2 Experiments and Analysis

In this section, in order to illustrate the merit of the new method presented in this paper, we experiments with the real sequence using the new method and the old one presented in Ref. [9]. These sequences are one from real cloudy background inserted synthetic targets and the others are airplane cut from military newsreel.

Real sequence: airplane is flying in the cloudy drifting sky. The white Gaussian noise is inserted into the sequence. Image size: 130 × 180 *pixel*, *SNR* = 1.48 dB.

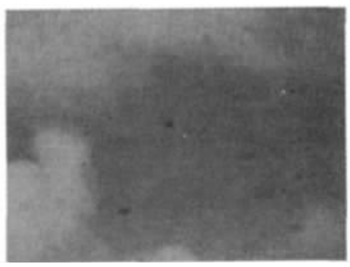

Fig. 2 One frame of the original real sequence with two targets

From Fig. 3 we can see that after the algorithm there are eight target traces are detected (the real target is marked with rectangular) . It can be found that the new method is more precise than the old method with fewer offset trace point from Figs. 4 and 5. The comparison of the two methods' performance can be seen as Tab. 1. For the multi-level matching and crossover operator operates on a rather high revolution and can adjust the offset point every three frame while in the old method this adjustment is carried out along the sequence without correction in time, hence this departure is amplified step by step.

Tab. 1 Error data association using different method for experiments sequences

Experiments sequences		Error data association(false target trace point)		
		Old method	New method	Error correction ratio γ /%
Real sequence	Target 1	3	1	66
	Target 2	9	0	100
Simulated sequence	Target 1	4	2	50
	Target 2	1	1	0
	Target 3	0	0	0

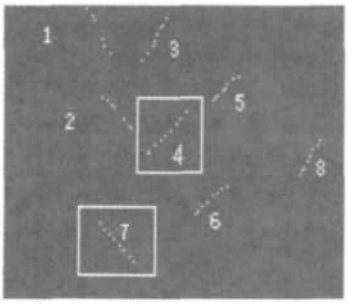

Fig. 3 The last detected targets

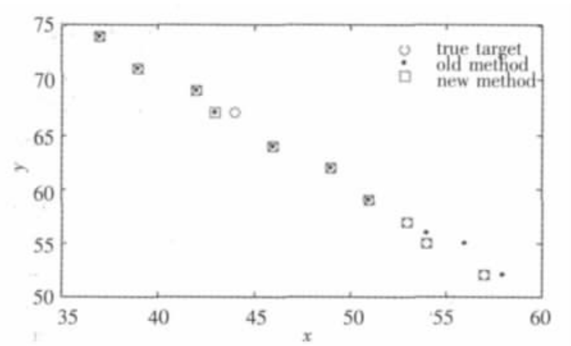

Fig. 4 The trace of target 1 with different methods

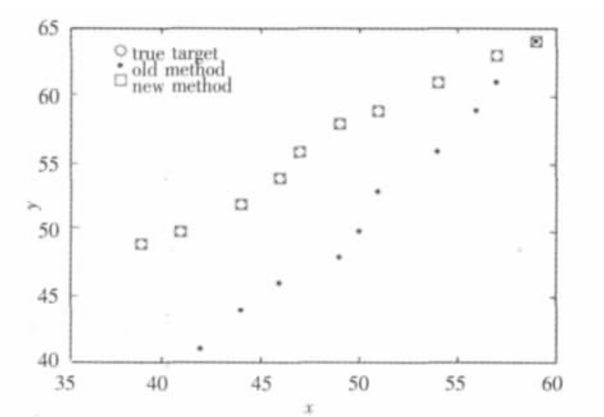

Fig. 5 The trace of target 2 with different methods

Simulated sequence: simulations have been done with synthetic target in real cloudy image sequence. Three targets are imbedded(as shown in Fig. 6) . One target moves in a 3D linear fashion, while the others follow 3D parabolic trajectory. Gaussian white noise is added into the sequence ($\mu = 0, \sigma = 1$) . The image size is 85×85 *pixel*, $p_{fa} = 10^{-9}$.

From Fig. 7 we can see that the target trajectory using new method (line) drifts off the real trace (dot line) in some point (marked with rectangular) . however, there is only one pixel offset between the detected and the true one (marked with regular) . It can be found that the offset is at the start or the end of the trajectory without the reference of precedent and ancestors for a short sequence.

Fig. 6 Original image with 3 targets are embedded

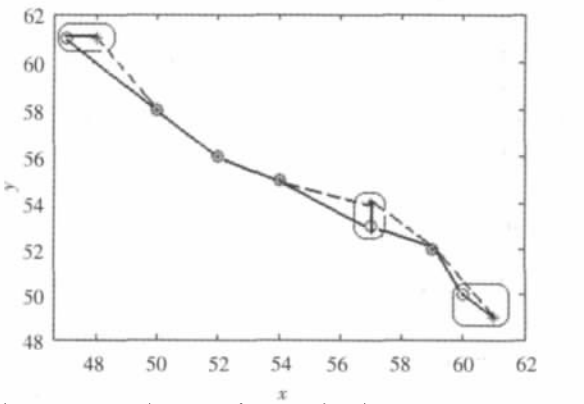

Fig. 7 The trajectory of target 2 using new method

In Tab. 1 for all the sequences we have a comparison of the error data association which reflects the performace of tracking using different methods. It can be seen that the new method have superiority in tracking and for each target trajectory 50% of the error data association created by old method can be corrected by the new method. Here the error correction ratio γ is defined as:

$$\gamma = 1 - \left| \frac{\textit{Error data association of new method-error data association of old method}}{\textit{error data association of old method}} \right| \times 100\% \qquad (7)$$

3 Conclusions

For dim Targets with low *SNR*, crossover and matching operator is presented in this paper. To overcome the demerit of DPA, we construct candidate segments according to greedy principle and based on the matching principle search the best matching link to form final trajectory set. Compared with the method in Ref. [9], the introduction of mult-level matching policy can strengthen the precise of tracking to some extend. Experiments and simulations results show that the algorithm performs very well in the presence of clutter and noise. If we have a long sequence, the offset as simulated sequence will be overcome.

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