

Dual-Module Data Fusion of Infrared and Radar for Track before Detect

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Abstract—A track before detect method based on data fusion of infrared and radar is proposed to increase the probability of correct track initiation and shorten initiation time. Track before detect is a new technique for dim target detection and tracking which is useful when the signal-to-noise ratio of target is low. Particle filter and dynamic programming for track before detect are currently proposed for detecting and tracking dim targets in low signal-to-noise ratio background. In this paper, we apply them in dual-module data fusion of infrared and radar. Particle Filter is applied to process the acquired data from radar. Dynamic programming is applied to process the acquired data from Infrared. Sensor receives data and generates the first stage decision. The decisions are subsequently transmitted to the fusion center where they are combined into a final decision on distributed fusion architectures. The proposed method is applied to simulate track before detect in dual module system of infrared and radar. The simulation results show that the proposed method increase the probability of correct track initiation and shorten initiation time.

Index Terms—track before detect, data fusion, particle filter, dynamic programming, probability of detection

I. INTRODUCTION

The dim targets are those have weaker RCS or smaller size in image, and therefore are difficult to be detected. With the development of the technology of antisense probe, the detection to dim targets is becoming an important problem in target detection technology. Track before detect (TBD) is a new technique for dim target detection and tracking which is useful when the signal-to-noise ratio (SNR) is low [1]. Traditional

tracking algorithms are designed assuming that the sensor provides a set of point measurements at each scan. In this case, the common approach is to apply a threshold to the data and to treat those cells that exceed the threshold as point measurements. A series of observation points is used to track targets. For low SNR targets the threshold must be low to allow sufficient probability of target detection, so false alert probability increases. Unlike the above approaches, TBD algorithm is actually as follows. The algorithm effectively integrates the measurements along possible target trajectories, returning as possible targets those trajectories for which the measurement accumulative value exceeds a threshold. Firstly, all the paths caused by the each scanning point are found out as possible track. Then all the measurement amplitude values of each path are added. Finally, the path whose accumulative value is larger than a threshold is found. TBD detections are not declared at each frame. Instead, after a number of frames of data are processed, the estimated target track is returned when the detection is declared. In the classical setup the measurements are the output of the extraction, see Fig. 1. In this setup there is a processing chain before the tracking [2]. This processing chain can consists of a detection stage, a clustering stage and an extraction stage. We see that in classical tracking

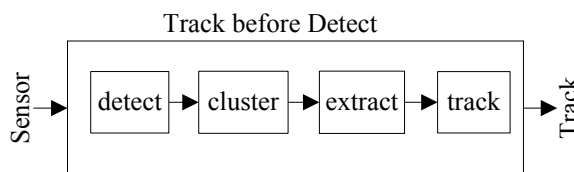


Fig.1 Classical data and signal processing (separate boxes) and TBD (large box)

threshold based decisions is already made directly on the basis of the raw measurement from one single scan. In TBD the decision is made at the end of the processing

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chain, when all information has been used and integrated over time.

Recently, several approaches for TBD are proposed for detecting and tracking dim targets in low SNR. Hough transform-based TBD algorithm is used to detect low observable target with constant velocity in K-distributed clutter and thermal noise [3]. These days, an alternative is to use TBD method based particle filter, or dynamic programming (DP) proposed for detecting and tracking targets in low SNR. Reference [4] analyzes a dynamic programming based track before detect algorithm. By using extreme value theory they obtain explicit expressions for various performance measures of the algorithm such as probability of detection and false alarm. But the DP process during the multi-frame integration causes the expansion of targets and strong noise which may produce a large amount of false targets. To reduce them, a new discrimination method which takes advantage of the feature of trajectory is proposed [5].

These algorithms are applied to detect optical images target in the past few years. Lately these methods are applied to detect and track radar target [6-8]. The maximum radar range is related closely with radar minimum detectable SNR. So, by applying TBD method, reliable detectable SNR of the radar can be decreased to about 7 dB, which means that the maximum radar range is increased around 40% [9]. The problem with using these algorithms is that it leads to high computation and memory resource requirements. Those methods are applied in single sensor system, radar or infrared.

Target recognition and tracking is an important research area in pattern recognition. However, single sensors (radar or infrared sensor) based on target recognition and tracking have their limitations. For example radar can provide complete position and Doppler information of the target. But it easily suffers from electromagnetic jamming due to its emitting electromagnetic waves. On the contrary, infrared has the powerful anti-jamming ability, it detects target by receiving thermal energy radiated from target without emitting any energy. Infrared, however, has the disadvantage of not being reliable in bad weather or other environmental conditions such as rain, dust and fog. Recently, the issue of precision guided munitions has been focused on using both infrared and mill-meter wave (MMW) radar for dual-model guidance. In this case, the infrared sensor serves as a complement to radar for guided munitions [10]. At present, multi-sensor data fusion has become the key technology for infrared and MMW radar dual-model guidance. Compared with single sensor, multi-sensor systems have more observables in the state space and extended coverage of time. The partly complementary information from the two sensors is able to improve the overall system performance [11]. So the sensor with lower performance can also meet requires in fusion system.

Here, we propose a track before detect method based on data fusion of infrared and radar to increase the probability of correct track initiation and shorten initiation time. Infrared and radar sensor subsystem work

independently, the acquired data of Infrared and radar is respectively processed, then each sensor brings decision of detection. At last decisions of sensor are subsequently transmitted to the fusion center where they are combined into a final decision on distributed fusion architectures.

II. PARTICLE FILTER ALGORITHM

An efficient method to implement such a TBD processing is provided by a particle filter. As this problem statement leads to a nonlinear non Gaussian filtering problem classical filtering methods. Kalman filtering will result in poor performance. A particle filter is used to deal with the nonlinearities and the non Gaussian nature of the noise. The same particle filter output is also used to perform detection based on a likelihood ratio test [12]. The method is better suited for tracking weak targets in noise than the classical method. Quite some subsequent work in this area has been performed recently, see reference [13]. Reference [14] gives details of a model setup and a particle filter based algorithm to deal with a multiple target track before detect situation. Reference [15] deals with target tracking for extended objects in a track before detect context.

A. Problem Description

Generally, filtering estimates system's states by using a series of its observation values. The nonlinear dynamic discrete system in the time domain can be expressed as:

$$x_k = f(x_k, E_{k-1}, v_{k-1}) \quad (1)$$

$$z_k = h(x_k, E_k, w_k) \quad (2)$$

$$x_0 \square p(x), E_0 \square p(E) \quad (3)$$

Where x_k is the state vector of the system at time k , E_k is the signal intensity, v_k is the process noise vector, z_k is the observation vector and w_k is observation noise vector.

B. Particle Filter

Particle filter is a reliable tool for object tracking because it neither limits to linear systems nor requires the noise to be Gaussian. It applies a recursive Bayesian filter based on propagation of sample set over time, maintains multiple hypotheses at the same time. Particle filter idea is to use some random sampling of discrete points (particles) to indicate approximately the probability density function with the state variables. When the number of sampling points is large enough, these particles can be a good sample as approximation of the posterior probability density function. Particle filter is a powerful and reliable tool for object tracking because it neither limits to linear systems nor requires the noise to be Gaussian. The realization process of particle filter involves the following five important steps:

Step1: Set $k = 0$, establish the initial state sample set $\{x_0^n, E_0^n\}_{n=1, \dots, N}$ in accordance with the objective movement model and observation model.

Step2: The importance of sampling. Posterior probability distribution can be attained by a group of discrete set of samples. Obtain a sample set of noise in accordance with the probability density function.

$$\tilde{q}_k^n = p(z_k | x_k^n, E_k^n, Z_{k-1}) \tag{4}$$

Step3: Compute the weights and normalize the weights according to (5).

$$w_k^n = \frac{\tilde{q}_k^n}{\sum_{n=1}^N \tilde{q}_k^n} \tag{5}$$

Step4: Calculate the lack of degree for particles take advantage of (6).

$$\hat{N}_{effect} = \frac{1}{\sum_{n=1}^N w_k^n} \tag{6}$$

If the value is less than the preset threshold, then it needs to resample sets of particles. One of the greatest problems for important sampling is the lack of the particle phenomenon. With the increase of time, the importance of weight may be concentrated upon a small number of particles, and then particles can not effectively express the posterior probability density function. To avoid this degradation, we applied resampling algorithm.

Step5: State estimate for the target.

$$\hat{x}_k = \frac{\sum_{n=1}^N x_k^n \cdot E_k^n}{\sum_{n=1}^N E_k^n} \tag{7}$$

C. Target Detection

In this section we will determine how to perform a detection of a possible target on the basis of the information provided by the particle filter. Given two hypotheses:

H_0 : No target present, $z_k = w_k$.

H_1 : Target present, $z_k = h(x_k, w_k)$.

We define the likelihood ratio.

$$\Lambda_k = \frac{p(z_k | H_1)}{p(z_k | H_0)} = \frac{\prod_{n=1}^N p(z_k | H_1)}{\prod_{n=1}^N p(z_k | H_0)} \tag{8}$$

We now declare a target to be present whenever the likelihood exceeds a threshold. The choice of a good threshold is a kind of compromise between false alarm probability and the probability of detection. False alarms is called that the likelihood exceeds the threshold when

no target is present. The probability of detection is called exceeding of the threshold when indeed there is a target present.

III. DYNAMIC PROGRAMMING

An alternative efficient method to implement TBD processing is provided by a dynamic programming [16,17]. Reference [18] presents a radar TBD algorithm of multi-target based on the dynamic programming which can exactly determine the number of targets, detect each target and separate the track of each target.

A. Dynamic Programming

Dynamic programming is actually a multistage decision optimization problem. The considered problem is divided into several sub-problems connected with each other when it is deal with. If the problem is regarded as a process, each sub-problem is a stage of the original problem. The state variables are introduced to describe the change of the process. The value of a state variable is called as a state and the value of the state is called as state set. States and state sets depend on stages. When states and the final states are determined, this process is fully determined. This means that the process can be represented as a series of states $\{x_1, x_2, \dots, x_k\}$, where x_1 is the initial state, x_k is the final state.

For a given optimal process, the value of some variable is required to choose so that the full process can become optimal according to the given principle. The selection of the state variables in each stage is the decision of the problem. Generally, the decision function is used to denote the decision process. The corresponding decision function series are called as strategy. The decision process must have a principle to measure whether the strategy is better or not and it is called as merit function. So, the problem can be reduced into the selection of strategy.

$$\{u_1(x_1), u_2(x_2), \dots, u_k(x_k)\} \in U \tag{9}$$

So the merit function becomes the biggest. The merit function is denoted by

$$f_k(x_k) = \max_{[u_1, u_2, \dots, u_k]} v_k \{u_1, u_2, \dots, u_k\} \tag{10}$$

where $f_k(x_k)$ is the optimal merit function or target function from the initial state to the final state.

B. The basic equations of dynamic programming

It is assumed that the merit function is the stage value and its form is

$$v_k(u_1, u_2, \dots, u_k) = \sum_{i=1}^k w_i(x_i, u_i) \tag{11}$$

where w_i is the stage index, denoting that in i stage the sate make decision, and u_i denotes the stage index function.

According to the optimal principle, we can get

$$\begin{aligned}
 f_k(x_k) &= \max_{\{u_i\} \in U} \left[\sum_{i=1}^k w_i(x_i, u_i) \right] \\
 &= \max_{\{u_i, u_k\} \in U} \left[w_k(x_k, u_k) + \sum_{i=1}^{k-1} w_i(x_i, u_i) \right] \\
 &= \max_{u_k} [w_k(x_k, u_k) + f_k(x_k)], \quad k = 2, 3 \dots M \tag{12}
 \end{aligned}$$

Where k denote the stage number of the decision process. In general, the initial condition can be assumed as

$$f_1(x_1) = w_1(x_1, u_1) \tag{13}$$

Thus, equations (11) and (12) are the basic equations in dynamic programming for several stages decision and this is actually a recursive relation equations.

C. Target detection based dynamic programming

TBD approach is a powerful technique for small target enhancement in the presence of clutter, with important applications such as the detection of small, dim targets in infrared detection and tracking system. TBD approaches are processing strategies designed to track a target of known characteristics through a sequence of images. The tracking process increases the effective target energy while simultaneously reduces the received noise. The performance gain is based on the SNR improvement that obtained from integration of the energy along its trajectory. These methods, 3D Fourier domain or sequential hypothesis, assumed that the target velocity was known. The DP algorithm effectively integrates the measurements along possible target trajectories, returning as possible targets those trajectories for which the measurement sum (merit function) exceeds a threshold. The threshold level is an important factor in system design, and theoretical curves are required to determine appropriate values. In the process of dim targets detection, the data is infrared images, range-doppler images, or orientation-frequency images from passive sensor. We suppose that infrared images at different time can be obtained from infrared sensor.

Usually the algorithm contains the following steps:

Step1. Initialization: for each state of the first frame $X_1 = [i, r, j, s]$, define the initial value of the merit function $X_1 = [i, r, j, s]$ equal to the measurement of the initial state, and initialize the function ψ_1 equal to 0. This function is used to map the state x_k to the most likely previous state \hat{x}_{k-1} , the state which maximizes the merit function $I(x_{k-1})$. Thus we can backtrack the trajectory.

$$I(x_1) = z_1(i, j), \quad \psi_1(x_1) = 0 \tag{14}$$

Step 2. Recursion: For $2 \leq k \leq K$, for all the $x_1 \in X_1$

$$I(x_k) = \max_{x_{k-1}} [x_k - 1] + z_k(i, j) \tag{15}$$

$$\psi_k(x_k) = \arg \max_{x_{k-1}} [I(x_k - 1)] \tag{16}$$

Where the maximization is performed over the x_{k-1} for which a transition to x_k is possible.

Step 3. Termination: For the threshold V_T , find

$$\{\hat{x}_K\} = \{x_K : I(x_K) > V_T\} \tag{17}$$

Step 4. Backtracking: For each \hat{x}_K , for $k = K - 1, \dots, 1$

$$\hat{x}_k = \psi_{k+1}(\hat{x}_{k+1}) \tag{18}$$

From this step we can get the recovered trajectory estimation.

The False Alarm and Detection probabilities can be formulated in terms of the merit function $I(x_k)$ as follows:

$$P_{fa} = \Pr_n(\max_{x_k} I(x_k) > V_T) \tag{19}$$

where $x_k \in \{\text{noise states}\}$, and

$$P_d = \Pr_{s+n}(\max_{x_k} I(x_k) > V_T) \tag{20}$$

Where $x_k \in \{\text{states within cell of the target}\}$. We assume that the merit functions are independent and Gaussian distributed.

D. Target measurement model

We consider the problem of tracking a point target that moves with constant velocity in the $x - y$ plane. An extended region surrounding the target is monitored by a measurement sensor, consisting of an $N \times N$ pixel of infrared image. The measurement in each pixel of the image at time k is $z(i, j, k)$, $i, j \in [1, N]$.

$$z(i, j, k) = f_T(i, j, k) + f_B(i, j, k) + v(i, j, k) \tag{21}$$

Here f_T is the measurement of target, f_B is the measurement of background, which is restrain by filter, and v is the measurement of noise.

$$f_T(i, j, k) = \sum_i^{Num(k)} A_i(k)h(i, j, x_i, y_i) \tag{22}$$

Here A_k denotes the target amplitude which will be assumed to be a constant for simplicity. The term $h(i, j, k)$ is the contribution in cell from the target, which depends on the point spread function of the windows, the target location, and the target intensity.

In many cases it is more convenient to deal with the likelihood ratio of the data, rather than the measurement probability density function. The pixels are assumed to be conditionally independent, and the likelihood of the whole image is simply the product over the pixels.

$$p(z(k) | x_k^i) = \prod_{i,j} p_{S+v}(z(i, j, k) | x_k^i) \tag{23}$$

Given two hypotheses:

H_0 : No target present.

H_1 : Target present.

We define the probability of the target occupying a particular location by the superposition of all of the possible paths to that position. An alternative is to use a Maximum Likelihood (ML) estimator. Rather than accumulate the probability from alternate paths, an ML estimator selects the single best path. An ML algorithm for discrete states is the Viterbi algorithm, which has been applied to TBD in [17].

$$L = L(z(0) \cdots z(k)) = \frac{p(z(0) \cdots z(k) | H_1)}{p(z(0) \cdots z(k) | H_0)} \quad (24)$$

IV. DATA FUSION

A. Data Fusion Model

The dual-model detection and tracking system is composed with infrared and mill-meter wave radar. In this case, compared with single sensor, multi-sensor systems extend coverage of space and time. The partly complementary information from the two sensors is able to improve the overall system performance. The multi-sensor data fusion has become the important technology for infrared and MMW radar dual-model guidance. In the process of targets detection, the data is infrared images from passive sensor, range-doppler images, or orientation-frequency images.

We process data on distributed detection fusion architectures. Infrared and radar work independently. Particle filter is applied to process the acquired data from radar. Dynamic programming is applied to process the acquired data from infrared. Finally, detection results are fused according to the rules in the fusion algorithm base. Fig.2 gives the data fusion system model.

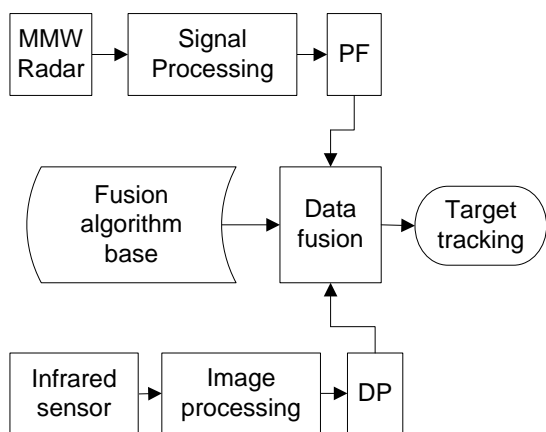


Fig.2 data fusion system model

We suppose that distributed detection fusion system is composed of fusion center and two sensors (radar and infrared). Each sensor, radar or infrared, receives a common volume data from target. Sensor processing receives data and generates the first stage decision. The decisions are subsequently transmitted to the fusion center where they are combined into a final decision about which the hypotheses is true. Assuming binary hypothesis testing for simplicity, we use $u_i = 1$ or 0 to

designate that sensor favors hypotheses H_1 or H_0 , respectively. The fusion procedure is that finding the Neyman–Pearson optimum distributed sensor detectors for cases with statistically dependent observations is described. These results clarify and correct a number of possibly discussions in the existing literature [19].

B. Fused detection probability

For the parallel Sensor, the globally optimal solution to the fusion problem that maximizes the probability of detection for fixed probability of false alarm when sensors transmit independent. If the Signal-to-Noise ratio of infrared and radar are S_i/N_i and S_r/N_r , we let the detection probability and false alert probability of infrared be P_{di} and P_{fai} , those of radar be P_{dr} and P_{far} . Then we let the detection probability and false alert probability of fusion system be P_d and P_{fa} . P_d and P_{fa} are given by the following equations, respectively:

$$P_d = P_{di}P_{dr} + P_{di}(1 - P_{dr}) + (1 - P_{di})P_{dr} \quad (25)$$

$$P_{fa} = P_{fai} + P_{far} - P_{fai}P_{far} \quad (26)$$

V. SIMULATION AND ANALYSIS

A. Target motion model

Generally, the sensor grid provides the necessary structure to model of the small target motion by the discrete process.

$$X_{k+1} = F \cdot X_k \quad (27)$$

$$X_k = [x_k \quad u_k \quad x_k \quad v_k] \quad (28)$$

Where $F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$.

Here, target motion state X_k are the discrete target positions and velocities, respectively and T is the time between successive sensor sampling. For simplicity we assume that $T=1$. Image frames number is a design parameter, chosen to encompass the velocity range of the target motion. The TBD estimation objective is as follows. Given the measurement sequence of L frames, determine the trajectories (state sequences) most likely to have originated from the actual target.

B. Simulation and analysis

In order to validate the performance of fusion system for track initiation, we address simulation for track initiation of radar, infrared, fusion system respectively. Furthermore we compare with performance of fusion system. We suppose that system acquire radar plot per

5ms and infrared plot per 10ms. The rule of track initiation is 5/7. Fig.3 and Fig.4 are the result of 100 time Monte Carlo simulation. Monte Carlo simulation results show that the fusion track initiation can increase the probability of correct track initiation and shorten initiation time.

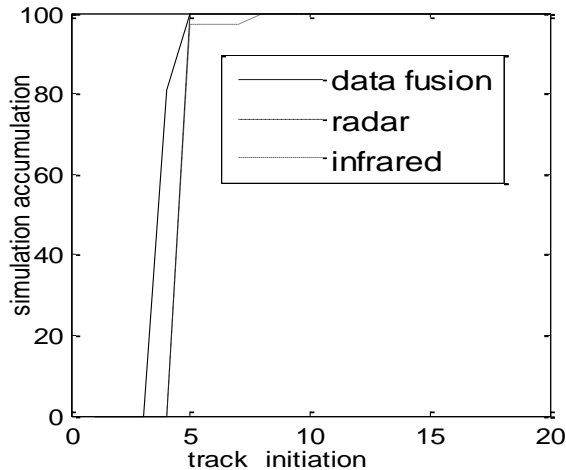


Fig.3 track initiation

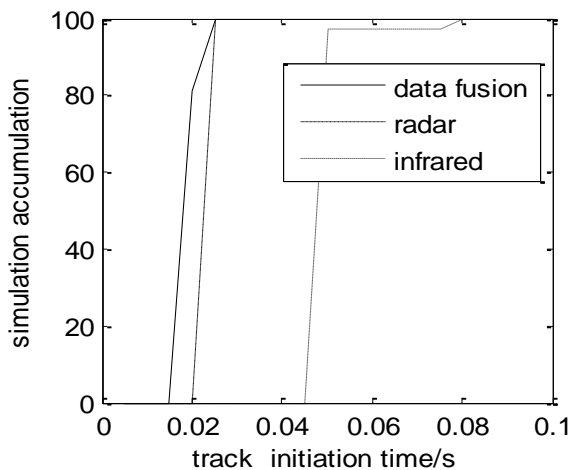


Fig.4 track initiation time

VI. CONCLUSIONS

In order to increase the probability of correct track initiation and shorten initiation time, we propose a track before detect method based on data fusion of infrared and radar. Particle Filter is applied to process the acquired radar data. Dynamic programming is applied to process the acquired Infrared data respectively. Sensor processing receives data and generates the first stage decision. The decisions are subsequently transmitted to the fusion center where they are combined into a final decision on distributed fusion architectures. The proposed method is applied to simulate track before detect of infrared and

radar. The simulation results show that the proposed method has advantages of probability of detection. Compared with a single sensor, the proposed method increases the probability of correct track initiation and shortens initiation time.

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