A Particle Filter Based Algorithm for State Estimation of Dim Moving Point Targets in IR Image Sequence

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Abstract—Under the condition of the targets’ initial information is already estimated successfully, this paper presents a real-time target tracking method based on particle filter (PF) update algorithm. According to the particles’ transmission characteristics and the measurements from a single frame detection, the algorithm estimate a target’s following moving state. In this way, the dim moving point target could be tracked successfully under the low signal-noise-ratio (SNR) in IR image sequence. But it comes to the multiple targets’ tracking, we should take the data integration into account. In order to reduce the amount of calculation, we use the data fusion method to divide the measurements in the overlapped parts of windows, appoints the measurements for the corresponding target. That is the Nearest Neighbor Standard Filter (NNSF) theory is used to choose the target for a measurement. The paper introduced the related theory and the concrete steps for accomplish the algorithm and also simulated the proposed tracking algorithm on the MATLAB platform. Experimental analysis and results showed that the algorithm achieved real-time, dynamic stability and robustness while track the random moving targets in high clutter environment.

Index Terms—particle filter, single frame detection, measurement division, state estimation, image sequence

I. INTRODUCTION

Tracking and detecting the dim moving point target under the background of low signal-noise-ratio (SNR) in IR image sequence become a research focus for its important practical significance. The purpose of target’s tracking is to find out the interest target in the time series. The target may be described with their own state, so the tracking problem is equivalent to give the target state solution, achieving by estimated theory. The target’s state estimated by the observation, for example, the target’s characteristics of gray, color, contour, and so on.

For intensive clutter in the IR image sequences, the dynamic system and observing noise may be non-linear and non-Gaussian, so there are some limitations in a linear system for target’s state estimation. Thus, it is important to include elements of non-linearity and non-Gaussianity, in order to model accurately the underlying dynamics of a system. To solve the problems, a lot of ways were provided. Expand Kalman Filter (EKF) method [1] is generally used. It adopted a linear transformation in a Taylor expansion to approximate the non-linear model, but the introduction of additional errors often caused the filter’s divergence. Nowadays, in order to deal with the state estimation problem under non-linear and non-Gaussian dynamic system, particle filter [2] [3] has been proposed, which applies to any state transition or measurement model, solving the nonlinear problems that may happen in the course of the target tracking. Particle filter is also called Bayesian Bootstrap Filter or Monte Carlo Filter, based on Monte Carlo random simulated theory. The system state is expressed by a group of weighted random samples, and a new state is produced via the iterative evolution of these random samples.

When the problem of state estimation for dim random moving point targets under the background of low SNR in IR image sequence, the algorithm proposed in this paper combined particle filter and the Nearest Neighbor (NN) theory, especially there are some targets. The joint probability data association (JPDA) [4] is taken an the best method to solve the multi-target problem, but it has a large calculation. In this paper we take a simple method, solving the measurement division problem that occur in the process of multi-target issue , at the same time, reducing the amount of calculation. Take the initial moving state of each target as priori information to produce the initial particles via sampling independently for each target. The tracker predicts the next state for the next single frame through particle filter.

Based on literature [5], this paper present an algorithm for tracking dim point target in IR image sequences with low signal-noise-ratio (SNR) background after the target’s initial position and velocity are already estimated successfully. Take the initial moving state as
priori information to produce the initial particle samples. Then according to the particles’ propagation and the measurements from a single certain frame detection, this algorithm estimate the targets’ following moving state frame by frame. In a word, the tracking accuracy has been guaranteed and at the same time, raising the possibility of real time operation.

II. OBSERVATION MODEL AND TARGET MODEL

Assume that the image sequence is a random process collected stably in time domain [5], but non-stationary in space domain. Time-domain smooth means that the image sequence has been corrected in space domain. Compared to the target, the changes of the background can be neglected. Non-stationary in the space domain, in other words, it means arbitrary nature background in image sequence. On these conditions, the observation model of dim moving point target in IR image sequence can be:

\[
Z (r, k, s) = S (\tilde{r}, k, s) + B (\tilde{r}, s) + N (\tilde{r}, k, s)
\]

Where \( \tilde{r} \) is \( \tilde{r} (x, y) \) in the two-dimensional Cartesian coordinates, \( S (\tilde{r}, k) \) is intensity affected by the target in pixel \( \tilde{r} \), \( k \) is the discrete-time sampling point, \( B (\tilde{r}) \) is short-term deterministic clutter background, \( N (\tilde{r}, k) \) is zero mean white noise, \( s \) express the randomness of the image sequence. Target model is given by:

\[
S (\tilde{r}, k, s) = \sum_{i=1}^{k_m} \sum_{j=-k_m}^{k_m} A_{i,j} \delta (\tilde{r} - \tilde{r}_{i,j}, t - k, s)
\]

Where the total number of the unknown targets at time \( k \) is \( k_m \), \( A_{i,j} \), \( \tilde{r}_{i,j} \) are the target’s unknown amplitude and location respectively.

III. FILTERING THEORY

The so-called filtering refers to “filter out” the target’s current state. It also means estimate the current state of target by the current and previous observations. The meaning of the particle filter is the posterior probability of a target’s state can be expressed by a number of particles. The proposed technique combined Bayesian filtering and the Monte Carlo method. Based on the assumption of linear system, Gaussian noise, the Kalman filtering and the Monte Carlo method. Based on the assumption of linear system, Gaussian noise, the Kalman equation, the Chapman-Kolmogorov equation:

\[
p(x_k/z_{1:k-1}) = \int p(x_k/x_{k-1}) p(x_{k-1}/z_{1:k-1}) dx_{k-1}
\]

Observe the posterior probability, which does not include the value at time \( k \), and it can be calculated from system state transition probability \( p(x_k/z_{1:k-1}) \).

Step 1: Update, that is by the systematic observation model and the observation \( z_k \) at the time \( k \), the posterior probability \( p(x_k/z_{1:k}) \) is derived from priori probability \( p(x_k/z_{1:k-1}) \). Access to observations \( z_k \), according to the Bayesian formula:

\[
p(x_k/z_{1:k}) = \frac{p(z_k/x_{1:k}) p(x_k)}{p(z_k)}
\]

Further simplification:

\[
p(x_k/z_{1:k}) = \frac{p(z_k/x_k) p(x_k)/p(z_k)}{p(z_k)}
\]

Among them, \( p(z_k/x_k) \) is the likelihood function, which gives the degree of similarity between system state transition and observations. \( p(x_k/z_{1:k-1}) \) is known as the a priori probability. \( p(z_k/z_{1:k-1}) \) is known as the Evidence, which is a normalization constant.

First of all, by prior probability \( p(x_k/z_{1:k-1}) \) at time \( k \) and system state transition model, predict the posteriori probability density \( p(x_k/z_{1:k}) \) of the system state, the moment of posterior probability, and then use the current observations \( z_k \) to amend it, in this way, get the posteriori probability density \( p(x_k/z_k) \) at time \( k \). After the posterior probability distribution \( p(x_k/z_k) \) of variables \( x_k \) obtained, in accordance with the principle of Monte-Carlo simulation, the
mathematical expectation of arbitrary function $g(\bullet)$ can be given as:

$$E(g(x_{0:k})) = \int g(x_{0:k}) p(x_{0:k}|z_{1:k}) dx_{0:k} \quad (6)$$

Can be used to approximate.

$$\bar{E}(g(x_{0:k})) = \frac{1}{N} \sum_{i=1}^{N} g(x_{0:k}^i) \quad (7)$$

In which, discrete samples $\{x_{0:k}^i, i = 0\cdots N\}$ is iid sequences which is generated from posterior probability distribution function. When $N$ is large enough, $\bar{E}(g(x_{0:k}))$ absolutely convergence on $E(g(x_{0:k}))$.

B Particle Filter

Particle filter is a practical algorithm to solve bayesian probability problem, also named conditional density propagation condensation algorithm, or bootstrap filtering or interacting particle approximations or sequential Monte-Carlo methods. SIS, SIR, ASIR, RPF and so on. The so-called particle, which is described as small-scale filter, can be considered a representative a point of the target’s state.

1) Sampling Importance Resampling Filter

The SIR filter proposed in [8] is an MC method that can be applied to recursive Bayesian filtering problems. The assumptions required to use the SIR filter are very weak. The state dynamics and measurement functions need to be known, and it is required to be able to sample realizations from the process noise distribution and from the prior. Finally, the likelihood function $P(z_k | x_k)$ needs to be available for pointwise evaluation (at least up to proportionality). The SIR algorithm can be easily derived from the SIS algorithm by an appropriate choice of (i) the importance density, where $q(x_{0:k} | x_{0:k-1}, z_{1:k})$ is chosen to be the prior density $p(x_k | x_{k-1})$, and (ii) Resampling step, which is to be applied at every time index.

The above choice of importance density implies that we need samples from $p(x_k | x_{k-1})$. A sample $x_k^i \sim p(x_k | x_{k-1}^i)$ can be generated. For this particular choice of importance density, it is evident that the weights are given by

$$\omega_k^i \propto \omega_{k-1}^i P(z_k | x_k^i) \quad (8)$$

However, noting that resampling is applied at every time index, we have $\omega_{k-1}^i = 1 / N, \forall i$; therefore

$$\omega_k^i \propto P(z_k | x_k^i) \quad (9)$$

The weights given by the proportionality in (9) are normalized before the resampling stage. As the importance sampling density for the SIR filter is independent of measurement, the state space is explored without any knowledge of the observations. Therefore, this filter can be inefficient and is sensitive to outliers. Furthermore, as resampling is applied at every iteration, this can result in rapid loss of diversity in particles.

However, the SIR method does have the advantage that the importance weights are easily evaluated and that the importance density can be easily sampled.

Using the prior distribution as the importance density is in some sense regarded as a standard SIR particle filter and, therefore, is an appropriate particle filter algorithm with which to begin. The SIR particle filter gives disappointing results with the low number of particles used here. The speckled appearance of the figure is a result of sampling a low number of particles from the (broad) prior. It is an artifact resulting from the inadequate amount of sampling. The RMSE metric shows a marginal improvement over the approximate grid-based filter. To achieve smaller errors, one could simply increase the number of particles, but here, we will now investigate the effect of using the alternative particle filter algorithms described up to this point.

2) Degeneracy Problem

SIS algorithm exists a fundamental problem is the Degeneracy Problem. After several times of forecasting and updating, all but one particle will have negligible weight, which is the particles’ degradation. Literature [62] pointed out that the weight variance increases over time, so degradation can not be avoided. To reduce the degeneracy phenomenon, Gordon, etc. [2] introduced a re-sampling algorithm. The basic idea is through the posterior probability density of re-sampling $N$ times, produce a new supported set $\{x_{k}^i, \tilde{w}(x_{0:k}^i)\}_{i=1}^{N}$, to retain or copy the particles that have greater weight, remove the particles which have smaller weight. Samples set $\{x_{0:k}^i, \tilde{w}(x_{0:k}^i)\}$ has been changed into $\{x_{0:k}^i, N^{-1}\}$.

By resampling [9], all of the particles have the same weight, thus avoiding the degeneracy.

The resampling step involves generating a new set particle. Adding random moment to these particles can forecast the state at time $k + 1$, which is system state transition process. At last, re-entering into systematic observation process and updating the state. At each discrete point in time (for each frame in image sequence), the particles are propagating by three steps: particle prediction (that is state transition), weight calculation and resampling. The sketch map of particle boosting in a frame is as following Fig.1 (eight particles as an example):

![Fig.1 The sketch map of particle boosting in a frame](image-url)
IV. THE DIVISION OF MEASUREMENTS

In the process of tracking, to reduce the computational complexity and improve computing speed, narrow the search range, measurements come from detecting in the windows, whose center is the forecast position. However, in the process of multi-target tracking, when various targets are far away, the impact among targets is small, we can use tracking method of single target to predict and update, but when the distance between the targets less than a certain value, tracking windows overlap. A situation occur that a measurement fall into the hands of a different tracking windows. Fig.2 shows this situation.

![Fig.2 measurements come into overlapping region](image)

**Crux of the issue is how to divide the measurements that come from the windows’ overlapping part. It is a question that a measurement in the overlapping part from which target. In multi-target states’ estimation, we based on the following assumptions:**

1) Each measurement has a unique source, that is, if one measurement was not from any target, certainly from the clutter.

2) For a given target, there is at most a measurement takes it as its source.

3) Take measurement 1 as an example, there is only one source, that is, if it is a measurement for a target. Then either is the measurement 1 for the target 1 or 2, or false alarm. In short, at this time, before input to the filter, it is necessary to divide the collection of measurements. In this paper, in order to reduce the complexity of algorithms, using the nearest neighborhood filtering thinking [10]. The basic idea is when a measurement is in overlapping regions, the distance between it and a target’s predicting location is the shortest, it could be the measurement for the target. That is, which has the smallest distance between the center of a window and the measurement as soon as the measurement for the tracking window. The smallest distance can be defined by Mahalanobis distance.

V. ABOUT CORRELATION MODEL

A. Target’s state transition model

Considering target tracking, the state transition model describe the moving properties of the infrared target between two frames. and the process has nothing to do with the current moment measurements. This step is a process of spreading priori probability. It is an assumption that the target state will propagate in which path. Whether a particle’s propagation is reasonable, it need the next step observation to modify. Far from the target, assume in a short period, the target dynamics can be approximated by straight-line track with constant velocity. So we can choose one order model as the state transition model. The equations can be written as:

\[
X(k) = F X(k - 1) + B w(k)
\]

(10)

\[
X(k) = \begin{bmatrix} x(k), y(k), v_x(k), v_y(k) \end{bmatrix}^T
\]

(11)

\[
F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}
\]

(12)

where \(X(k)\) is state vector, \((x(k), y(k))\) and \((v_x(k), v_y(k))\) are respectively the target pixel position and velocities at time \(k\), \(B\) is particle’s propagating radius, \(T\) is the interval between two image samples, and \(w(k)\) is zero mean Gaussian white noise process at time \(k\).

B. Probability observation model

In many cases, it is often use target features like contour, color, shape, texture, color distribution and size to describe a target. However, infrared targets are generally have no clear contour and color information. Here, we only use target’s gray values and moving information to describe.

1) Single frame detection based on target’s gray level information

At present, multi-frame detection tracking technology is common used in dim moving target-tracking in image sequence, or sequential testing tracking technology. As these test tracking technology needs to confirm the measurements by multi-frames, but this will lead to real-time problem. To improve the real-time of tracking system, this paper present a method based on single frame detection technology. That is the tracking technology gets measurements from a single frame. To reduce the amount of computation, first we should determine the target’s possible moving region, where we detect the possible target measurements.

\[
Frame_{k-1}(i, j) - Frame_k(i, j) > 3* \sigma
\]

(13)

\[
Frame_{k-1}(i, j) - mean(\text{frame}_k) > 3* \sigma
\]

(14)

Here, first we must calculate the local regional variance: \(\sigma\) and mean: mean. If (13) or (14) sets up, it is judged to be the possible target points. In above equations, \(Frame_k(i, j)\) is the \(k\) th frame at a certain pixel.

2) The establishment of observation probability model

Observation model [11] is to verify the state transition system’s results via measurement data, in fact, it is a process of measuring the similarity. As each particle represents the possibility of target’s state, the purpose of systematic observation is to give a particle which is more
similar to actual situation a large weight, and which is large different to actual situation a smaller weight. Systematic observation is the image at time \( k \). Getting characteristic measurements from single frame detection. Since the target is too small and in low signal to noise background, there are still many false alarm targets in the detection window. First of all, the measurements data should be fused, then calculating the residuals information of each particle to the measurement, in this way, each particle’s weight can be obtained from (15):

\[
\omega_k^{(n)} = P (Z_k | X_k^{(n)}) = \frac{1}{\sqrt{2\pi}} e^{(R^{-1}v)^2/2} 
\] (15)

In which, \( v \) is the residuals information, and \( R \) is the covariance.

VI. STEPS OF TARGET’S STATE ESTIMATION

Given moving parameters, one particle is on behalf of a possible moving state, and that is likely to the target’s location. At each time \( k \), the target’s parameters can be approximated with weighted particles. That is the posteriori filtering output. For combining the particle filter, the tracking algorithm has the characteristics of multi-peaks, so it has very strong robustness. Through the propagation of these particles, the trajectory of target can be obtained. The tracking framework is described in Fig.3:

Under the framework of particle filter tracking theory, the steps of estimation for a target’s state are as follows(Take a target as an example):

1: Initialization: At time \( k = 0 \), taking the target’s initial moving information as a prior distribution \( p(x_0) \).

According to the initial state information \( p(x_0) \), establishing samples \( \{x_0^{(n)}, N^{-1}, n=1\} \), \( N \) is the number of particles.

2: State transition: According to the samples \( \{x_{k-1}^{(n)}, N\} \) at time \( k-1 \), through the state transition function (16), receiving samples \( \{x_k^{(n)}\}^N_{n=1} \) at time \( k \).

\[
X(k | k-1) = F \cdot X(k-1 | k-1) + BW(k) 
\] (16)

The essence of state transition system is adding disturbance on the position coordinates, that is the propagation of particles in space. It forecasts the particles’ state at \( k \) th frame.

3: Single frame detection: At time \( k \), open tracking windows (the target’s possible moving region) on the \( k \) th image according to the dispersion of particles, then search in the window point by point by (13) or (14), and then search in the window point by point. Measurements can be obtained.

4: Measurements division: When the targets’ trajectories are crossing, in particular, the tracking windows are overlapping, we must resolve the associated problems. And then using NN approach to divides all the measurements to corresponding target, in other word, it is finding their own measurements for each target. We can get each target’s integration measurement \( \tilde{Z}(k) \) at time \( k \).

5: Calculating residuals:

\[
V(k) = Z(k) - \hat{X}(k | k-1) 
\] (17)

6: Computing weight: According to the residuals in a single image from (17), computing the weight \( \omega_k^{(n)} \) of each particle by (15), and then they were normalized into \( \omega_k^{(n)} = \omega_k^{(n)} / \sum_{n=1}^{N} \omega_k^{(n)} \), we can get a set support point:

\[
\{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} 
\]

7: Target’s state Updating: Using the set of points \( \{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} \) to calculate the target’s posteriori state:

\[
\hat{X}(k) = \sum_{n=1}^{N} x_k^{(n)} \omega_k^{(n)} 
\] (18)

8: Resampling: According to weight \( \omega_k^{(n)} \) of each particle, resample \( N \) times from \( \{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} \).

Concrete process is as follows:

a). Compute the cumulative weight of the particle set: \( \{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} \), that is \( C_k^{(n)} = C_k^{(n-1)} + \omega_k^{(n)} \);

b). Produce random number \( u \), where \( u \) is a uniform distribution on the interval [0,1];

c). Search among set \( \{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} \), find the smallest \( j \) that is making \( C_k^{(j)} \geq u \), and then do \( x_k^{(n)} = x_k^{(j)} \). A new set support points can be obtained:

\[
\{x_k^{(n)}, \omega_k^{(n)}\}^N_{n=1} 
\]

9: Increase \( k \), return to step 2, the tracking system accept the next frame. Repeat the process until all the images have been disposed.

VII. SIMULATION RESULTS AND ANALYSIS

When only one target is in the view field, there is no interference from other target, so we can directly adopt particle filter to predict and update the targets’ states.
when there are multiple targets, particularly, targets’ trajectories are crossing, which involves measurements division problem. This article uses the nearest neighboring theory to divide the measurements. Because there is no JPDA’s complexity, the algorithm is simple, but it also solved the issues about attributive division of measurements.

A. A single target situation

A real 200-frame-infrared (240×320) image sequence was used to test the algorithm performance. In the experiments, taking infrared sky as the background, adding one dim point moving target and Gaussian white noise. The target size is 3×3-pixel size. In a short period of time, the target’s gray information do not change, and a constant velocity for moving. In one image, we almost cannot determine a point target’s location with our eyes, so add a window on the target to track.

Parameters are as follows: Tracking window size is 11×11-pixels, SCNR=3, the probability of detection is 0.98. The first few frames can determine the target’s initial priori position information, the initial location of particles uniformly distribute within a window. Sampling the image sequence one by one, and estimating target’s state frame by frame. The initial state is: \(X_0 = [48.5, 48, 0.55, 1.5]\). Process noise covariance: \(Q = \text{diag}(0.005^2, 0.005^2)\). The greater the particle propagating radius and number of particles, the higher the tracking precision, but this will lead to the increase of calculation. Taking the requirements of real-time into account, the calculation of the tracking system should not be too large. We weight the tracking precision and the calculating complexity, the number of particles \(N = 200\), and the propagating radius of particles \(B = 1\).

Based on those parameters, this algorithm track point target in image sequence with signal to noise ratio is 3 or more.

Fig. 4 shows the tracking result. The algorithm can track the target with random trajectory in high clutter environment; it realized the reliable tracking for the target. From Fig.5, we can see the number of measurements in a single frame image through detecting. The number is small. It means less false alarm targets, improving the reliability of the tracking system. Fig.6 reflects the comparison between true trajectory and tracking trajectory. The solid line is the real target trajectory, and the dotted line is the estimated track trajectory. Fig.6 is position estimation error curve, horizontal axis direction and vertical axis direction respectively, namely, with the time increase of image frame index the change of the estimated position error.

B. Multiple targets

There are multiple targets, whose trajectories are crossing, parameters are set as above simulation. Adding three dim point moving target and Gaussian white noise. The difference between single-target state estimation and multi-target states estimation lies mainly the time trajectories crossing. Tracking windows overlap each other. This time related to measurements division. Using NN approach to divides all the measurements to corresponding target, in other word, it is finding their own measurements for each target. The experimental results are as follows:

Fig.7 the tracking results, from left to right are: 50th, 160th, 180th frame of image sequence
The algorithm can track the targets with random trajectories in high clutter environment; it realized the reliable tracking for the multi-target. Fig.4 reflects the comparison between true trajectories and tracking trajectories. The solid line is the real target trajectories, and the dotted line is the estimated track trajectories.

From Fig.9 to Fig.11 are position estimation error curve, horizontal axis direction and vertical axis direction respectively, namely, with the time increase of image frame index the change of the estimated position error. The position error $\text{Error}$ is defined as:

$$\text{Error} = |X - \hat{X}|$$  \hspace{1cm} (19)

In which, $X$, and $\hat{X}$, are the target’s real states and estimated states respectively.

Tracking target successfully with this paper’s algorithm has showed visible effectiveness and tracking accuracy in the course of the estimation for the targets’ next state , but when the target change the direction suddenly or the target is almost overshadowed by background , the error between true trajectory and estimated trajectory is become larger. However, there is no loss of target and remain track the target effectively, when the target comes out again, the algorithm can restore the previous tracking performance. The target’s position estimation error is similar to a pixel. The estimation algorithm has led to very good tracking results for trajectories undergoing abrupt changes in noisy situations. It’s also a very good solution to the target’s loss problems in the course tracking. In particular, this method not only has a good tracking performance, but also real-time in a high degree. Simulation results shows that the algorithm, basing on the particle filter and measurements from a single frame image, is robust for tracking dim point target in IR image sequence.

VIII. CLOSING REMARKS

In this paper, a new algorithm, basing on particle filter and single frame real-time detecting, for implementing the targets’ states estimation has been presented. Also we give a discussion on multi_target tracking. When comes to measurements division, we focus on the Nearest Neighbor method. It was applied to tracking dim moving point targets in IR image sequence, and simulation results showed that the proposed algorithm assured the tracking accuracy, at the same time, real-time performance has been very good met effectively in tracking dim moving point target in image sequence.

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