Detection and Tracking Algorithms for IRST

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Abstract

Infrared search and track system is an integral part of modern weaponry. The detection and tracking algorithm forms the heart of an IRST system and their effectiveness plays an important role in determining performance of the system.
This report studies various detection and tracking algorithms for multiple point targets in noisy environment resulting in very low signal to noise ratio. Target detection is carried out using spatial-temporal techniques needing multiple frames, since targets are assumed to be irresolvable in a single image frame. The tracking algorithms are classified in the basis of different approaches for data selection and model selection. Data selection and model selection is used for tracking multiple targets in dense clutter environment. An overview of the Interacting Multiple Model Expectation Maximization algorithm, and brief description of Multiple Hypothesis Tracking and Joint Probabilistic Data Association Filter algorithm is also presented.

Keywords: IRST, IMM-EM, JPDAF, MHT.

1. Introduction

The ever-increasing effectiveness of electronic warfare and the advent of anti-radiation missiles create the need for covert, radar silent operations. Therefore systems are required which are virtually immune to jamming, undetectable and yet capable of detecting targets at reasonable ranges. The infrared search and track system (IRST) is the most suitable choice for such scenario. IRST is a system that surveys environment by analyzing the infrared radiation, emitted by the targets compared to background. The major work of the IRST is detection and tracking of target. In a practical scenario target are not in ideal conditions, they are generally surrounded by clutter. Hence so detection and tracking is much more complication in practical scenario.
The developments of efficient clutter rejection algorithms are important to detect the targets in the modern IRST systems. In low signal to noise (SNR) situation, the target could not possibly be localized on the single frame so the successive frames are used to detect the target. If the alignment is done properly the signals of the various images would add up and a signal with suffiently large SNR are achieved, while the noise will be cancel out. This approach of detection of dim target is usually referred as target before detection (TBD) and generally used for detection of dim targets.

Tracking is the estimation of the state of the moving object based on the remote measurement. It uses models of the real environment to estimate the past and present and even predict the future. The use of a tracking system is to extract information from a dynamic system. A track is a symbolic representation of a target moving through an area of interest and represented by a filter state which gets updated on each new measurement.

2. IRST system

It is becoming common for passive electro-optical sensors to be included in the design of airborne and terrestrial military platforms. Passive electro optical sensors are valued for their lack of sensor emissions, electronics countermeasures immunity. IRST system is wide field of view passive electro optical surveillance system designed for autonomous target detection and track acquisition. An IRST system uses thermal sensor to detect targets. A typical IRST system as shown in fig.1 have thermal detector which receives the thermal signatures of the target. The thermal signature is then processed by font end electronics and given to the tracker. The function of the tracker is to detect and tracking the target and give coordinate information to the servo control unit for controlling the sensor head. The control and display unit is a user interface with the system, where the target information is displayed.

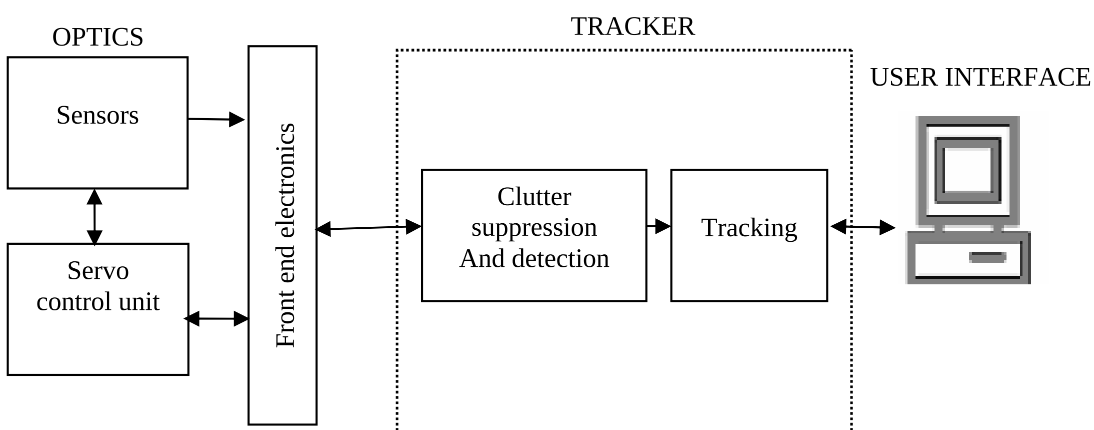

Fig 1. Infrared search and track system

3. Target Detection

To introduce the concepts involved in target detection, the simplest case consists of a sub-pixel target in uniform Gaussian noise. Because the target does not take up the whole pixel, the signal from the target pixel consists of the target signal and Gaussian noise from the background. The output for the pixel at (i,j) with the target present is given by

$$Y(i, j) = t + N(0, \sigma)$$

and with target absent

$$Y(i, j) = N(0, \sigma)$$

Where Y(i,j), is the pixel signal, t is the target signal and N(0,σ) is a Gaussian distribution with zero mean and standard deviation = σ. A detection threshold, T, is usually set to be a multiple, k, of the background standard deviation, i.e.

$$T = k\sigma$$

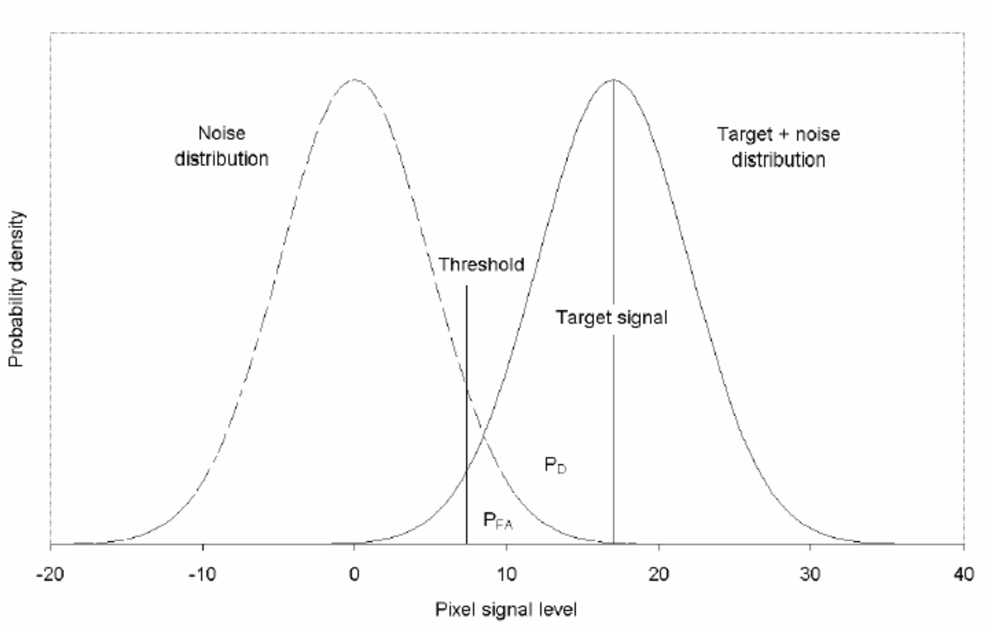

Fig.2 Target and noise probability distribution [2]

Representative distributions of the target and noise signal, and an assumed threshold, are given in Fig.2. The noise distribution has zero mean, by definition, and the target distribution is the noise distribution shifted by the value of the target signal. The probability of detection, PD, is the integral of the target distribution above the threshold, and the probability of false alarm, PA is the integral of the noise distribution above the threshold. The integral of the target distribution below the threshold is the probability of missed detection.

The next simplest case is where the standard deviation of the background varies over the image. If a constant threshold was used the false alarm rate would vary over the image. A constant false alarm rate (CFAR) can be obtained by setting the threshold based on the local standard deviation evaluated over a sub-window of the image.

The most complex case is where the background consists of rapidly varying clutter which varies in both mean and standard deviation. It is then necessary to use a filter to suppress the background clutter and enhance the response of the target. The aim is to generate an output from the filter which is a field of Gaussian white noise containing target peaks. The previous methods can then be used to detect the targets.

One approach to target detection is to use a matched filter. The filter weights are chosen to give an increased response from the filter when the target is present and a decreased response when clutter is present. When the target is single pixel in size the clutter suppression becomes more important. Another approach is to carry out a smoothing operation which removes the salt and pepper noise from the image. This smoothed image is subtracted from the original image the result is a collection of point-like objects which may contain a target. Basically there are two classification of filter in image processing and the others are derivates of them.

3.1 Classifications of detection system

There are two models for a target detection system. The track-after-detection system (TAD) and Track before detect (TBD).
The TAD involves a target detection process to produce position estimates of possible targets in a single frame, which are passed to a tracker to produce likely target trajectories. The TAD method can work well when the target is bright, but not suitable for dim targets.

Track-before-detect (TBD) method is used, when the target is dim there is not enough information in a single frame to allow detection of a target. In this case, simplified tracking procedures are combined with detection procedures to increase the discrimination between targets and backgrounds. In this method a number of frames are used to accumulate gain enough information of the targets for proper detection.

3.2 Issues involve in IRST algorithm (TBD)

1. Effective Adaptive Spatial-Temporal Technique for Clutter Rejection
2. Optimal nonlinear filtering for track-before-detect in IR image sequences.

3.2.1 Effective Adaptive Spatial-Temporal Technique for Clutter Rejection

The adaptive spatial temporal clutter rejection technique is based on a multi-parametric approximation of clutter which, after estimation of parameters, leads to an adaptive spatial- temporal filter. The coefficients of the filter are calculated adaptively to guarantee a minimum of empirical mean-square values of the filtering residual noise for every time moment. The adaptive spatial-temporal filtering algorithm allows one to suppress any background, regardless of its spatial variation. Simultaneously, the algorithm estimates LOS drift and allows for jitter compensation [3].
This detection scheme consists of two algorithms, clutter rejection and jitter compensation. The first one is based on the multi-parametric approximation of clutter by decomposing it as a sum of products of unknown parameters and given spatial basis functions. Parametric methods involve the assumptions about the structure of the clutter statistics, which are represented by the models with adjustable parameters. The Fourier basis or wavelet basis may used as basis function. In the algorithm, these parameters are estimated along with the jitter according to the maximum likelihood principle. Since the support of the basis and the number of terms in the sum are chosen in advance, so this is a *Fixed Support algorithm* (FS-Algorithm). The second algorithm is based on the spline approximation where not only the parameters of the approximation, but also the support of the approximation, are unknown. A simple example of such approximation is a step-wise constant approximation in unknown domains. In this case, not only the amplitudes, but also the domains, should be estimated. This algorithm is known as an *Adaptive Support algorithm (AS-Algorithm).*

3.2.2 Optimal nonlinear filtering for track-before-detect in IR image sequences

The 3D matched filter proposed by Reed et al.18 and its generalizations (e.g. banks of assumed velocity filters (BAVF)) provide a powerful processing technique for detecting moving low observable targets. This technique is a centerpiece of various track-before-detect (TBD) systems. However, the 3D matched filter was designed for constant velocity targets and its applicability to more complicated patterns of target dynamics is not obvious. The 3D matched filter and BAVF are extended to the case of switching multiple models of target dynamics. The 3D matched filtering can be cast into a general framework of optimal spatial temporal nonlinear filtering for hidden Markov models. This is a robust and computationally efficient Bayesian algorithm for detection and tracking of low observable agile targets in IRST system. The structure of TBD algorithm consists of two parts tracking and detection. Tracking is performed by utilization of the optimal (nonlinear) Bayesian filter (ONBF), for detection a modified Generalized Likelihood Ratio (GLR) is used.[4]

3.3 Comparison of spatial-temporal and spatial filter

The performance of the spatial temporal filter is shown in the Fig.3. The picture on the left hand side shows a typical input (clutter and noisy) frame. The picture on the right side shows the output of spatial temporal filtering, with temporal window T=20. Fig. 4 shows the results of spatial filter for the same input. The statistics for the both the filters are shown in the table 1.

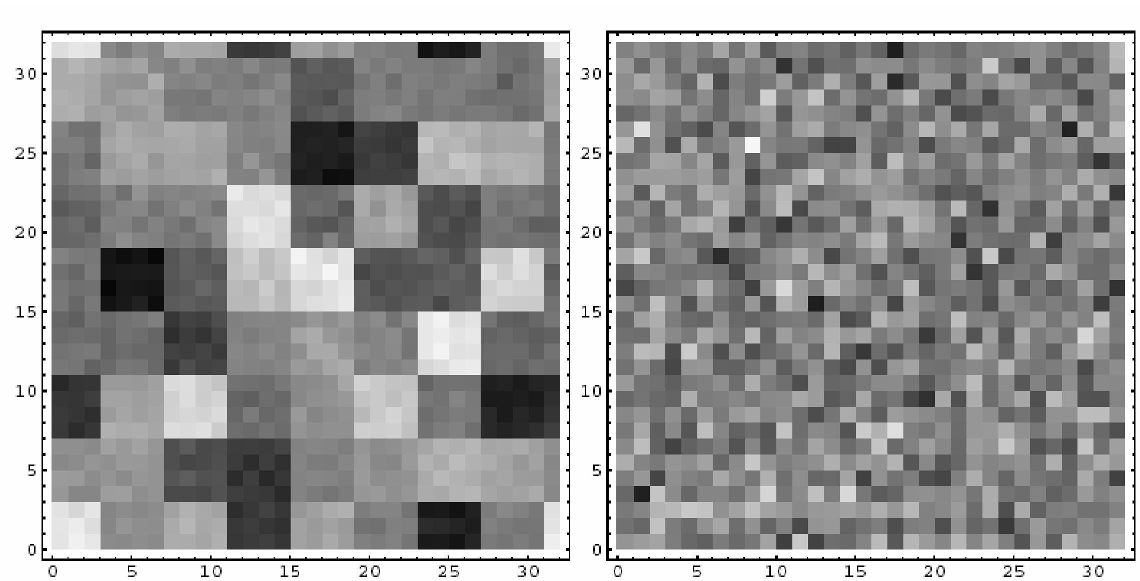

Fig. 3 clutter rejection spatial- temporal filter [3]

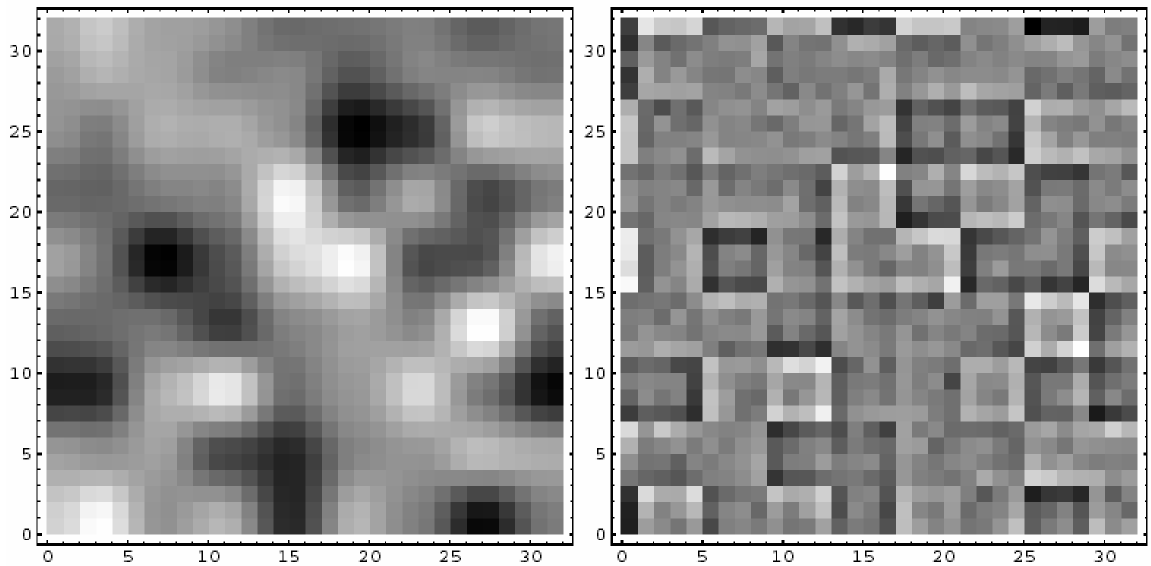

Fig. 4 clutter rejection: spatial nonparametric filter [3]

	Minimum	Maximum	Mean	Variance	Gain
Input	3.04	105.25	56.10	482.86	
Output(spatio-temporal), T=20	-10.24	9.44	-0.011	10.84	16.5(db)
Output (spatial)	-36.34	34.60	-0.004	114.99	6.2 (db)

Table 1 comparison of spatial-temporal and spatial filter [3]

4.1 Multiple targets tracking system

A typical multiple target tracking system (MTT) is shown if Fig 5. Signal processing unit converts the signals from the sensor to measurements, which become the input data of the MTT system. The incoming measurements are first considered for the update of existing tracks. Gating tests evaluate which possible measurements to track pairings are reasonable and a more detailed association technique is used to determine final pairings. Measurements not associated to existing tracks might be potential candidates for initiating new tentative tracks. When the quality of the measurements is high enough, a tentative track becomes confirmed. Similarly the low quality measurements become deleted. The tracks are predicted ahead for the next iteration and the processing cycle repeats.

A gate based upon the maximum acceptable measurement plus tracking predicted magnitude is placed around the predicted track. Only those observations are within the gate are considered for update of the track. When closely spaced targets produce closely spaced observations there will be conflicts such that there may multiple observations within a track's gate and an observation may be within the gates of the multiple tracks. This is handled by observation-to-track association and track maintenance functions**.** Recursive processing is typically being used and tracks are formed on previous tracks.

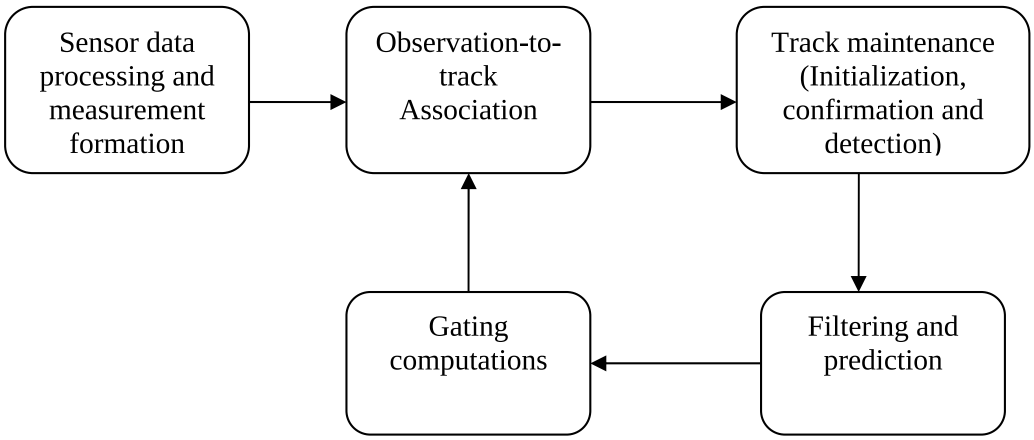

Fig. 5 Typical multiple target tracking system

4.1.1 Estimator

Estimation is process of selection of a point from a sample space. The sample space may be continuous and discrete. More precisely estimation is a process of defining a probability distribution over a sample space. *Decision* is a process of selection of one particular value from sample space based on estimated probability density function. This value is optimal in some sense. The optimality criterion is defined with a *cost function.*
Generally the process of estimation and decision are dealt as a single process is referred as an estimation process.
A measurement at time instant k is denoted as z(k) and the measurement set containing all measurements unto time k is denoted by Z^k.

Measurement z(k) is function of state x as

z(k) = h(k,x,w(k))

Where w(k) is measurement disturbance at time k.
An estimator is a function from measurement Z^k to some value $\hat{x}$ that estimate the true state x in some sense

$\hat{x} \triangleq \hat{x}(k, z^k)$

An estimate is particular value of the estimator function induced by the received measurements.

An likelihood function $\Lambda(x)$ describes how likely the measurements z(k) gives x

$$\Lambda(x) \triangleq p[z^k / x]$$

A maximum likelihood is the estimate the value that maximize the above likelihood function and given by

$$\hat{x}^{ML} = \arg\max_x \Lambda(x) = \arg\max_x p[z^k / x]$$

Maximum a posterior estimate takes into account the prior distribution for the random variable x
This is the Baye's theorem and given by

$$\hat{x}^{MAP} = \arg\max_x p[x / z^k] = \arg\max_x p[z^k / x] p[x]$$

4.1.2 Data association

The formation of target tracks in a mulitarget environment is confounded by a significant degree of uncertainty in the origin of target measurements. The procedure used to handle the measurement origin uncertainties is called the data association. The data association task can into two parts i.e observation-to-observation (track formation) and observation-to-track association or track maintenance.

4.2 Tracking

Tracking of targets with less-than-unity probability of detection in the presence of false alarms, data association is crucial. Tracking uses models of the real environment to estimate the past and present and even predict the future. The use of a tracking system is to extract information from a dynamic system A track is a symbolic representation of a target moving through an area of interest. Internally, in the tracking system, a track is represented by a filter state which gets updated on each new measurement.

Tracking in a multi-target, clutter is characterized by uncertainty in the origin of the measurements. The tracking function consists of
1. Estimation of the current state of the target (i.e. filtering) based on uncertain measurements selected according to certain rules [1]
2. Calculation of accuracy (usually covariance) and credibility associated with the state estimation.

4.2 Tracking algorithm

4.2.1 IMM-EM algorithm

IMM-EM (interacting multiple model expectation maximization) algorithm involves EM based tracking algorithm using interacting multiple models.

This algorithm is divided into two major parts. In the first part, the state is filtered using EM algorithm, and the likelihood model is calculated for each model. . It is followed by an IMM step, which updates the combined state estimate, the model probability, and predicts the state for the next time instant. The centroid of the measurement is used for evaluation the model probability [5].

4.2.1.1 Interacting multiple model algorithm

In the Interacting multiple model (IMM), uses multiple models that interacts through state mixing to track a maneuvering target. The IMM consists of filter for each model. It evaluates model probability for each filter and it is used for mixing state estimate of the target. In IMM, for each target many filters based on different model are initialized.

4.2.1.2 EM algorithm

EM is an iterative optimization method to evaluate target state estimate using the previous states estimate. This algorithm has two steps E-step and M-step. E-step can be interpreted as constructing a local lower-bound to the posterior distribution, whereas the M-step optimizes the bound, thereby improving the estimate for the unknowns.

4.2.1.3 Algorithm steps

In IMM algorithm to find the model probability of each model, it is required to find the likelihood of an observation.

N_t = targets present during the complete sequence of image frames

$\phi_{t,k}$ = combined state estimate at time instant k for target t

$\phi_k^m(t)$ = state at time instant k by model m for target t

Y_k = observation process at time instant k

N_k = number of measurements obtained at time k

Z_k = association process at time instant k

M = total number of models used in the IMM algorithm.

First the centroid $y_k^t(t)$ of the observation for target t at time instant k is calculated. This step is executed only once before starting the EM iteration. As soon as the observation set is available, the assignment weight $\hat{z}_k^t(t)$ is calculated and it is used to $y_k^t(t)$ given by

$$y_k^c(t) = \frac{\sum_{i=1}^{N_k} \hat{z}_{k,i}^{(0)}(t)\, y_{k,i}}{\sum_{i=1}^{N_k} \hat{z}_{k,i}^{(0)}(t)}$$

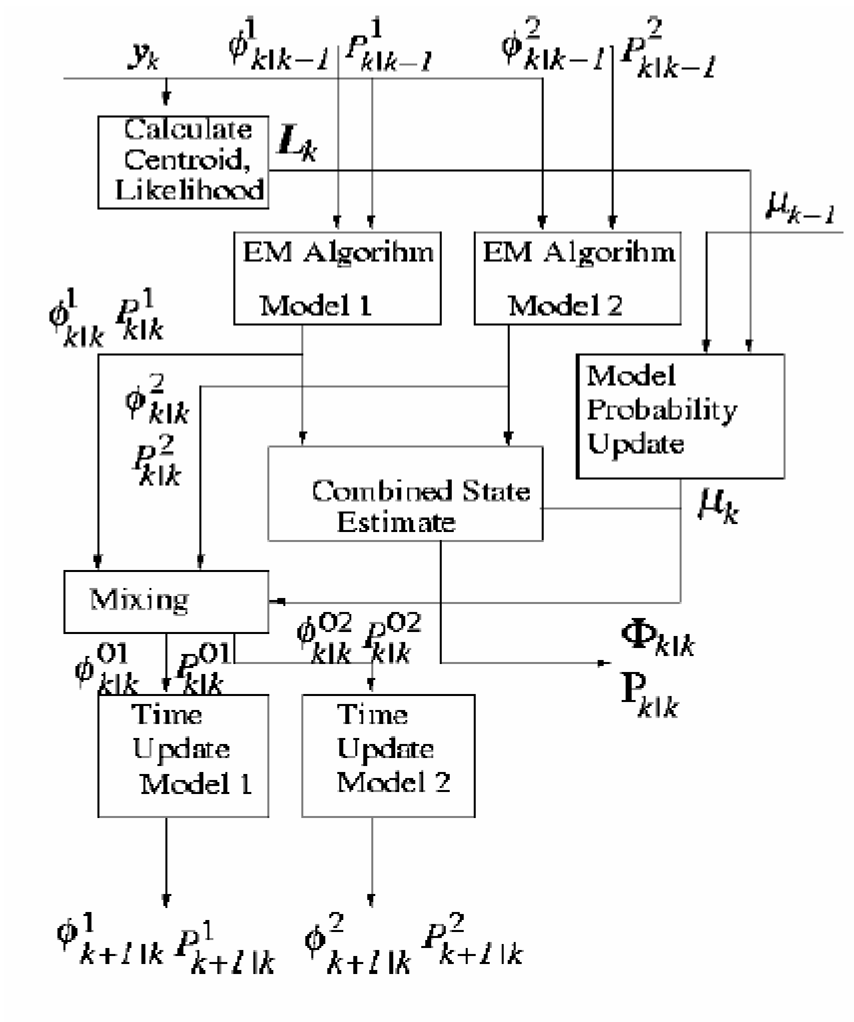

Fig. 6 IMM-EM algorithm for two models

Based on this centroid of observations, the model likelihood is calculated and it is used to evaluate the model probability. The centroid of observation $y_k^t(t)$ is not used for state estimation of the target. In Fig.6 shown the IMM-EM algorithms for two models, in which L_k and P_k represents the likelihood and covariance calculated at time instant k.

The IMM-EM algorithm operates as follows

As the current set of observation y_k become available, following two steps are performed at time instant k:

(i) The observation set y_k is validated using combined state prediction $\phi_{k/k-1}$ for a given target.

(ii) EM step is evaluated sequentially for each target and for each model of a given target, which are interlinked with each other through assignment weights. After completion of EM step, for each target IMM step is executed.

4.2.2 Multiple Hypothesis algorithm (MHT)

MHT is a deferred decision logic in which alternative data as association hypotheses are formed whenever the observation-to-track situations occurs, Rather than choosing the best hypotheses, or combining the hypotheses as in the JPDA, the hypotheses are propagated in a future in anticipation that subsequent data will resolve the uncertainty [6]. In the MHT, the hypotheses are carried over from previous scan. Then on the receipt from the new data, each hypothesis is expanded into a set of new hypotheses by considering all observation to track assignments for the tracks within the hypotheses. Fig 7. illustrate the logical overview of MHT algorithm. The family structure (node) provides convenient mechanism for implementing MHT.

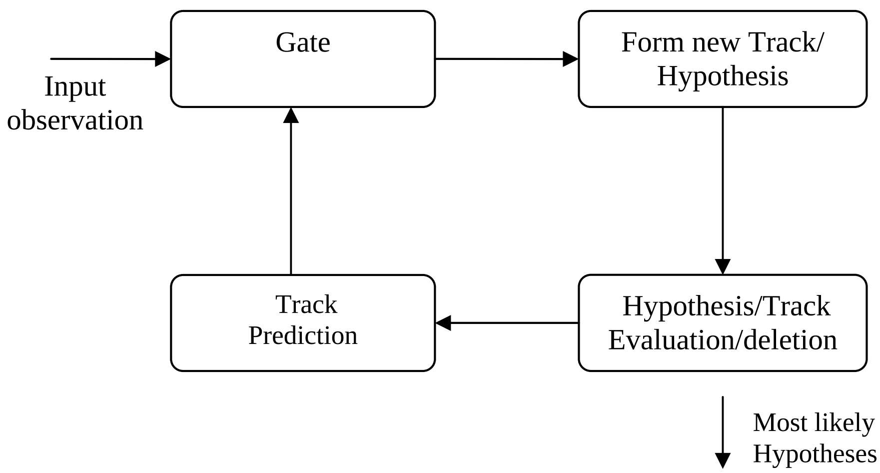

Fig 7. MHT logic overview

4.2.3 JPDA algorithm

The joint probabilistic data association (JPDA) algorithm is used to track multiple targets by evaluating the measurement-to-track association probabilities and combining them to find the state estimate

Two simple solutions for track update are strongest-neighbor filter (SNF) and the nearest-neighbor filter (NNF). In the SNF, the signal with the highest intensity among the validate measurements (in a gate) is used for track update and the others are discarded. In the NNF, the measurement closest to the predicted measurement is used. While these simple techniques work reasonably well with benign targets in sparse scenarios, they begin to fail as the FA rate increases or with low observable (low probability of target detection) maneuvering targets. Instead of using only one measurement among the received ones and discarding the others, an alternative approach is to use all of the validated measurements with different weights (probabilities), known as probabilistic data association (PDA) [7].

The PDA algorithm calculates in real-time the probability that each validated measurement is attributable to the target of interest. This probabilistic (Bayesian) information is used in a tracking filter, the PDAF, which accounts for the measurement origin uncertainty.

4.4 Comparison

MHT performance is comparable to the conventional single hypothesis (GNN) method at 10 to 100 times the false alarm density of the GNN, but it is computationally complex algorithm and not suitable for the real time systems.
JPDAF algorithm is less complex and faster the MHT algorithm. IMM-EM can successfully tack maneuvering and non-maneuvering targets simultaneously. It takes less time than JPDAF and it is suitable for real time applications.

5 Conclusion

The detection algorithm should have jitter compensation technique for detecting the target with low false alarm so the adaptive spatial temporal algorithm is preferred over the other. IMM-EM is faster algorithm which is suitable for implementing in real time application. So the combination of these two algorithms will result a robust and reliable system.

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