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EXPLANATION OF MULTIPLE TRACKING TARGETS IN MTI RADAR AND ITS FILTERING WITH KALMAN MODEL AND IMM ALGORITHM

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ABSTRACT

Since the tracking of moving targets is a fundamental concern in military and civilian applications, aerospace industries are always studying for exact, low-error, computationally light, and uncomplicated algorithms for target tracking. Nowadays, most modern military systems are equipped with numerous sensors. The perfect operation of such sensors helps to achieve target tracking. Due to the nature of the sensor system and the types of noises, one kind of sensor alone cannot be perfectly used in target tracking. Consequently, several different sensors are operated in new systems for tracking.
The present study aims to explain the multiple tracking targets in MTI radar and its filtering with the Kalman model and IMM algorithms. Also, applied algorithms for tracking moving targets using phased array radar are discussed. Various algorithms are proposed in this field, including interacting multiple models (IMM), Kalman filter (KF), and extended Kalman filter (EKF). These simple and multi-rate algorithms are reviewed in detail.

Keywords: multiple tracking targets, MTI radar, filtering, Kalman model, IMM algorithms

INTRODUCTION

Tracking means being aware of information about the change of position, velocity, and direction during different movement phases. Knowledge of the exact position of a target at a specific time is realized with electro-optical and radio wave (electromagnetic) methods and radars. The most useful radar for this purpose is the phased array radar, capable of accurately detecting the elevation angle, orientation, and height, as well as the distance information between the target and the antenna without mechanical rotation of the antenna. The role of phased array radars in the country's aerospace surveillance network to meet military and civilian needs is very prominent. To detect the current position and speed of the target, we need to track and predict the path. The main elements of any tracking system are data allocation, trajectory prediction, and filtering.

The first and most famous application of MTT was the track-while scan (TWS) system described in Hovanssian's book [1]. The TWS system is a special sub-branch of the MTT system in which data is received in the form of a regular time sequence through a regular sensor sweep. For common TWS systems, the search and update operations are performed simultaneously. At a constant rate, a sensor monitors new targets and tracks targets with the same observation time, the same detection threshold, and the same waveform. TWS systems only retain traces within the system's pre-defined search range.

In most modern systems, several different sensors are used for tracking. Radar systems are used to accurately measure the angle and range of targets. However, they cannot measure the target angle with proper accuracy. On the other hand, infrared search and tracking (IRST) sensors can measure the angle of the target with high accuracy and determine the direction of the target completely. However, it is not easy to detect the target range for IRST.

Providing a structure to integrate the information of these sensors facilitates the exact location of the target and also tracks the change of the target location. IRST emits infrared rays to search and track targets, such as jet planes and helicopters. IRST gains awareness of the environment with the vision of infrared rays. Such systems are passive and do not emit any radiation, unlike radar. The advantage of this method is not identifying the system itself.
This study aims to address the practical algorithms of tracking moving targets using phased array radar. Various algorithms are proposed in this field, including interacting multiple models (IMM), Kalman filter (KF), and extended Kalman filter (EKF). These simple and multi-rate algorithms are reviewed in detail.

Multiple tracking targets

The main components of the MTT system based on TDS

MTT system does not suffer from the limitations of TWS systems. For example, data can be received at irregular intervals. Traces can be kept even in unsearched areas to find new targets. Also, the observation time and detection threshold in these systems change adaptively.
With the emergence of electronically scanned antenna or phased array antenna, new MTT systems have entered a new era of progress. Phased array radars can send the beam to any desired point without the inertia problem of mechanical moving antennas. This gives radars adaptive sampling. Therefore, the transition from search mode to find new targets to refresh view mode is done almost in real-time. Also, in this type of radar, the sampling time can be reduced to a few milliseconds. Therefore, phased array radars have the possibility of sampling at a very high rate. This gives the phased array radar the potential ability to track multiple targets. At the same time, the usual TWS systems use mechanically scanned antenna and are strongly affected by inertia. In addition, in phased array systems, the array can be divided into several sub-arrays and $\sum$ and Δ signals can be used to measure the exact angular position of the target, similar to the mono pulse method. It is also possible to measure the exact angular position of the target by irradiating several beams consecutively through the canonical scan method. The use of the latter capability in the phased array system has led to the formation of the track during the scan algorithm [2]. In this research, the capabilities of this algorithm in tracking targets with high maneuverability have been investigated.
Figure (1) represents the components of an MTT system. There is a significant overlap between the operations of these components. However, such a representation provides a simple division of MTT operations suitable for introducing this system.

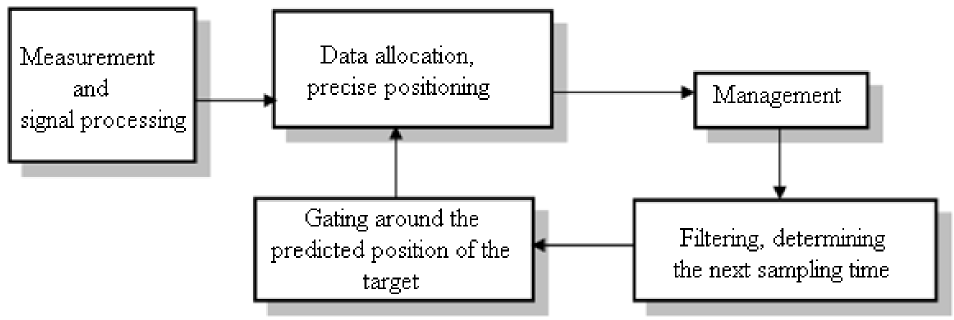

Figure 1: The main components of an MTT system

The processing loop of Figure (1) is executed repetitively by receiving data from the measurement block and processing the signal. As soon as the data is entered, data-tracking correspondence is done in two steps. First, through the Gating Test, a cursory allocation of data to reasonable tracks is done. Then the data allocation algorithm performs the final refinement and finally assigns data to each of the tracks. Unallocated data is nominated to form new potential tracks. The tracking management block decides about them. This block also decides whether to keep or delete a track based on the assumed quality of the tracks. After the data allocation stage, the address of the cell containing the target is determined. The radar can measure the precise angular position of the target by radiating several beams to the desired cell. After completing all these operations, the data is filtered and the next sampling time (for algorithms with adaptive sampling time) is determined. Then, the future position of the targets is estimated to form the gates around these positions. The time intervals between observations in non-array systems are fixed and predetermined. In this way, the processing loop is completed once. As soon as the data is entered, this loop is repeated recursively. Below the operational tasks of the blocks are examined in more detail.

1. Input data

It is assumed that the signal processing block performs the process of detecting the return signal of the targets and sends the resulting information to the display screen. As a result, bright spots appear on the screen. Some of the spots represent targets and the rest represent false alarms. To generate the input data, the radar grid screen is simulated and its information is stored in a matrix. The entries of this matrix are "0"s and "1"s. The values of "1" represent the presence of the target in the corresponding cells. Also, the value "0" represents the absence of the target in the corresponding cells. The simulation of the radar screen is done as follows.
1. Cell dimensions are determined based on the power of resolution in coordinate directions.
2. Cells containing the target are lost with probability $1-P_D$.
3. In cells without a target, a false alarm appears with probability P_{Fa}.

2. Gating

Gating is the first stage of the data allocation algorithm. As soon as an observation is assigned to previously formed tracks or a new track, the following procedure for decision is realized.
1. Refreshing the previous tracks. An observation may apply to the gate of one or more previous tracks. In this case, the desired observation is tracked as a candidate for allocation to it.
2. Being a candidate for forming a new tracking. The observation received may not apply to any of the gates. In this case, the desired observation becomes a candidate for forming a new track.
Figure (2) shows the gating process for two targets close to each other. At the same time, the gates of two targets close to each other may overlap. In general, gating is done in the form of the following steps.
1. Estimating the target's next position.
2. The formation of gates around the center of estimated points for the next position of the targets. The size of the gate is proportional to the result of the measurement error and the

estimation error. The bigger the errors, the bigger gates are selected, and vice versa. The geometric shape of the gates is also important. On the one hand, we want the data related to the desired tracking to fall inside the gate with a high probability. On the other hand, the size of the gate should be the smallest to prevent false processing and waste of radar resources.
3. Checking the presence or absence of received data inside the gate.

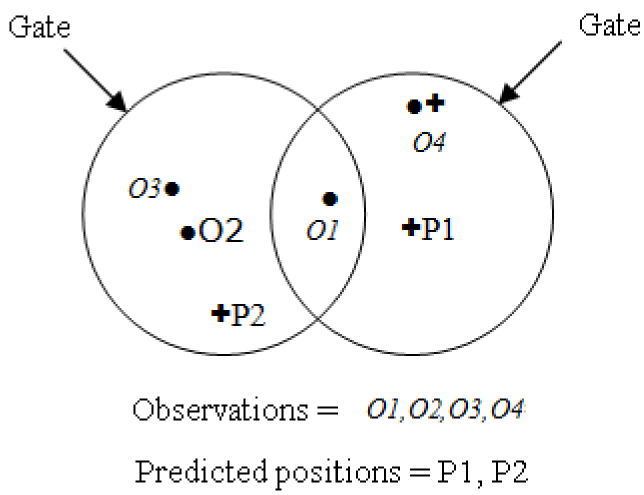

Figure 2: Gating two close targets

Due to the high observation refresh rate and subsequently the low estimation error, a search is usually not performed in each refresh of phased array radars. As a result, the antenna is radiated in the estimated direction and the search process takes place in the range. Therefore, gating is done on the range. This reduces the tracking load in multi-operational phased array radars.

3. Data allocation and accurate positioning
After gating, the data allocation operator performs the final data-tracking correspondence. If there is only one observation at the gate of a track, data allocation is very simple. For distant targets, it is not easy to make a decision. Several observations may be placed in the gate of one track, or one observation may apply to the gate of several tracks. In such situations, there are two main solutions:
1. Nearest neighbor approach. A maximum of one observation (the closest observation to the center of the gate) is used to refresh the tracking. The observations are assigned to the tracks in such a way that the sum of the distances of the assigned observations from the center of their corresponding gates is the smallest.
2. All neighbors approach. All valid observations in the gate of a track are used to refresh that track. As a result, the center of gravity of all observations inside the gate is used to refresh the tracking. Observations close to the center of the gate with more weight and observations further away with less weight participate in the calculation of the center of gravity. For example, in Figure (2), the weight of O1 for refreshing T2 tracking is less than the weight of O2 and O3. In phased array radars, after determining the data allocation status, the exact position of the target can be measured with the help of the methods mentioned in the first section, and these accurate data can be used to refresh the tracking.

4. Tracking management
Observations not assigned to previous tracks can be used to create new tracks. Also, a special restriction can be applied that if an observation is placed in the gate of a track (even if the data allocation algorithm in the nearest neighbor method does not use this observation to regenerate its corresponding track), that observation is not used to create new tracks. Also, it is not possible to be sure with a single observation that the new target is within the search range of the system. This observation should be confirmed in subsequent scans. The reason is that there is a possibility that this observation is a false alarm. So it is necessary to confirm a received

observation at least once to form a new track based on this observation. Gate size and refresh time for this observation is a function of the accuracy of the initial observation. A simple and conventional method to stabilize the tracking is to assign M observations to the desired tracking in N times of scanning the search area. The commonly used tests are three observations out of four scans or three observations out of five scans.
Unrefreshed tracks lose their quality and should be deleted. A simple method for this is to delete a track after scanning, provided that no observations are received to refresh the desired track. You can also use the method based on the time elapsed since the last refresh.

5. Filtering

Two major techniques for multiple tracking targets are linear techniques and non-linear techniques. Filters with constant coefficients (β-α and γ-β-α) and Kalman filter (KF) are grouped in the class of linear filters. Filters with fixed coefficients have fixed gain coefficients for different maneuvering conditions. Such coefficients are applied taking into account predetermined criteria. As a result, such filters have a simple computational structure and are useful in systems with limited radar resources dedicated to the filter block. On the contrary, the Kalman filter uses variable coefficients for the filter gain. Such coefficients are calculated adaptively for different maneuvering conditions. The most famous nonlinear technique used in MTT systems is the developed Kalman filter. This technique is used in case of non-linearity of the measurement process model or non-linearity of the target dynamic model. According to the above content, the block diagram of a data processing system can be represented in Figure (3).

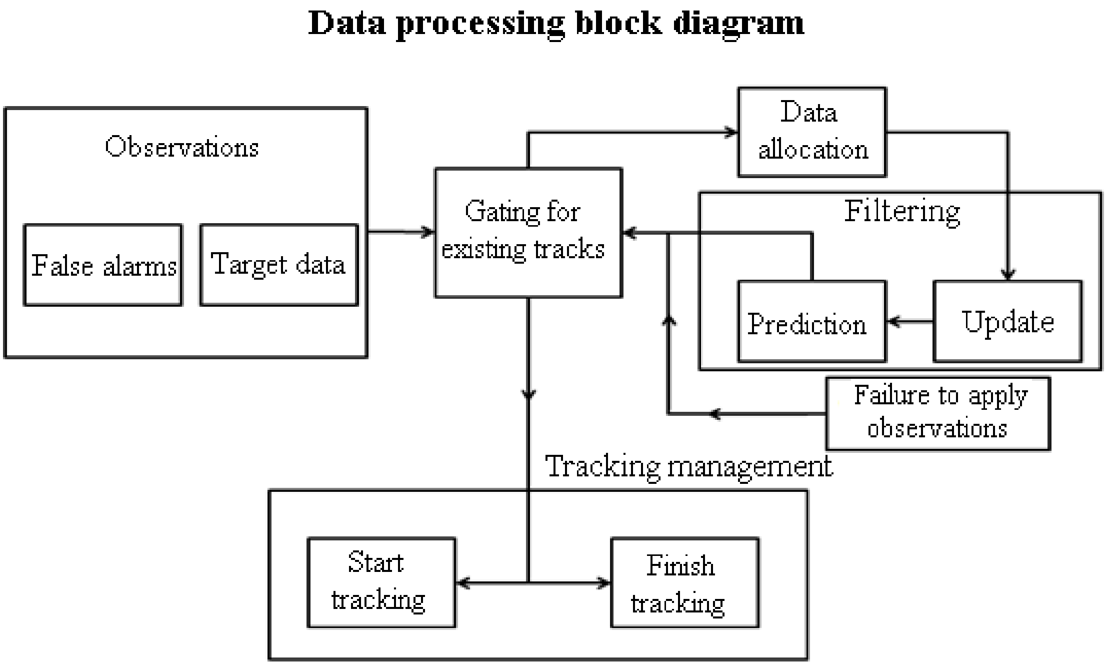

Figure 3: Block diagram of TWS tracking loop [3]

Another important issue in multiple tracking targets is the selection of the coordinate device and state vector in this device. Also, splitting and decomposing a track into one-dimensional tracks along the coordinate components is one of the prominent issues in multiple tracking targets. Decomposing a multi-dimensional track and turning it into several one-dimensional tracks performs the necessary calculations on scalars instead of matrices and leads to significant savings in the number of necessary calculations [4].
Each of the above techniques can be used with fixed or variable sampling time. The variable sampling time is specific to phased array systems. Before describing the above filters, estimation methods are discussed as the basic principles of filters.

6. Estimation

This section deals with the estimation of dynamic systems and the study of their formulas in

discrete time. Estimation techniques are divided into Bayesian and non-Bayesian. Statistical techniques are used both for non-Bayesian methods such as maximum likelihood (ML) and for simple Bayesian methods. In certain circumstances, they may even produce similar results. In Bayes's estimation, it is assumed that the unknown parameters have a posterior distribution.
A common method in state estimation is the least squares (LS) method, which focuses on minimizing the mean squared error according to the following formula.

$$\hat{x}^{LS} = \arg\min_{x} \sum_{i=1}^{t} (y_i - h(x))^2 \qquad (1)$$

This concept is realized for random parameters by minimizing the desired value in the observations $y_t = [y_i]_{i=1}^{t}$.

$$\hat{x}^{MMSE} = \arg\min_{x} E\left\{(\hat{x} - x)^2 \mid Y_t\right\} \qquad (2)$$

This relation is known as minimum mean square error (MMSE). It can be easily shown that the above relation is calculated from the following conditional expectation.

$$\hat{x}_t^{MMSE} = E\left\{X \mid Y_t\right\} = \int x p(x \mid y_t) dx$$

According to Bar-Shalom (1988) [5] if the conditional expectation is expressed in differential form, its derivative is calculated based on equation (3):

$$\frac{\partial}{\partial \hat{x}} E\left\{(\hat{x} - x)^2 \mid Y_t\right\} = 2(\hat{x} - E\left\{x \mid Y_t\right\}) = 0 \qquad (3)$$

Maximum likelihood (ML) is a statistical method also known as the general likelihood function. The estimation is considered the maximum likelihood ratio. The problem of estimating parameters and random states of a noise system has been studied by researchers for a long time. The general theory for non-linear filtering with non-Gaussian noise as well as a comparison of the linear and non-linear form of Bayes theorem is discussed in Jazwinski (1970) [3].

7. β-α filter

The β-α filter assumes a constant speed maneuver for the desired target. This assumption holds even for accelerated targets, as long as the sampling time is small enough. The β-α filter is defined by the following return relations:

$$\hat{x}(k+1,k+1) = \hat{x}(k+1,k) + \alpha[z(k+1) - \hat{x}(k+1,k)] \qquad (4)$$

$$\hat{v}(k+1,k+1) = \hat{v}(k,k) + \frac{\beta}{qT}[z(k+1) - \hat{x}(k+1,k)] \qquad (5)$$

$$\hat{x}(k+1,k) = \hat{x}(k,k) + T\hat{v}(k,k) \qquad (6)$$

where α and β are constant gains of the filter. z(k+1) is the received observation at the nth moment and T is the time interval between successive refreshes. The q parameter is equal to 1 in normal conditions. However, at the time of no data finding, q is the number of scans performed after receiving the last observation. The initial conditions for these filters are set as follows.

$$\hat{x}(1,1) = \hat{x}(2,1) = z(1) \qquad (7)$$

$$\hat{v}(1,1) = 0 \qquad (8)$$

$$\hat{v}(2,2) = \frac{z(2) - z(1)}{T} \qquad (9)$$

8. Infrared detectors

After the emergence of solid-state technology, infrared sensors entered a new era. In reference books, infrared detectors are classified in different ways, such as fast and slow detectors, high-power and low-power detectors, detectors operating in time and frequency space, and photonic and thermal detectors.

The first type of infrared system was a single-element system equipped with a mechanical scanner. This system monitors the desired target and shows a light spot. Usually, the detectors used in this type of system are quantum detectors in the range of 3-5 micrometers. According to the type of detector used in these systems, the image is formed as a light spot from the target. The detector observes a point of the target due to the presence of the emission source. This point is projected by the searcher's optics on an array and the scanning system sends orientation information to the control circuits. Until now, various search engines have been designed and built with this technology. Today, point infrared detectors are used in tactical missiles. As a result, to overcome the problem of false targets, it is very important to optimize the characteristics of the detector. Among the point infrared searchers used in missiles, Tow anti-armor missiles or Stinger anti-aircraft missiles can be mentioned.
It is necessary to be very careful in the construction of the elements of this type of detector to obtain a uniform and homogeneous response. Also, the electronic balance must be achieved artificially. To obtain a wider field of view with maximum spatial resolution, the number of FPA elements should be increased. Also, the system should be designed in such a way that large deviant signals from the background can be detected.

9. Kalman filter

Kalman filter is the most common adaptive filter for estimating time-varying parameters in tracking problems. This filter is a linear estimator grouped in the class of Bayesian estimators. Unlike classical estimators, Bayesian estimators have some initial information about the desired parameter and estimate the desired parameter by having previous information. The important thing about Bayesian estimators is that the improvement of this category of estimators compared to classical estimators relies on the accuracy of previous information. The more accurate the previous information is, the more efficient the estimator will be. On the contrary, if the previous information is inaccurate, not only the estimation quality does not improve, but the performance of Bayesian estimators becomes worse than classical estimators. In addition to the Kalman filter being optimal according to the least squares error, this filter also has other flexibility that makes its use in tracking systems inevitable. One of these capabilities is the calculation of the gain coefficient in an adaptable manner for different maneuvering conditions. The gain rate can be modified in the absence of data finding. The covariance matrix of the state vector is recursively calculated in each step. This matrix can be used in the stage of gating and data allocation. In the Kalman filter, the effect of data misallocations can be partially compensated.
In the Kalman filter, the first-order Markov process is used to model the movement of the target [6].

$$x(k+1) = F(k)x(k) + v(k) \qquad k = 0,1,\dots \qquad (1\text{-}3)$$

where x(k) is the state vector of the system and v(k) represents the noise vector of the system, which is used to include the uncertainty of the model. The components of the vector v(k) are a sequence of the normal process with zero mean and variance σ_v^2. The covariance matrix v(k) is a positive definite matrix and each eigenvalue is proportional to the uncertainty value of the corresponding parameter.
Figure (4) shows the Kalman filter processing loop. According to this figure, the recursive relations of the covariance matrix are independent of the observations and independent of the system state. Therefore, they can be calculated offline. This is vital in reducing the computing load of the processor. Instead of calculating the covariance matrix in each step, the value stored in the memory is used, which significantly reduces the amount of calculations.

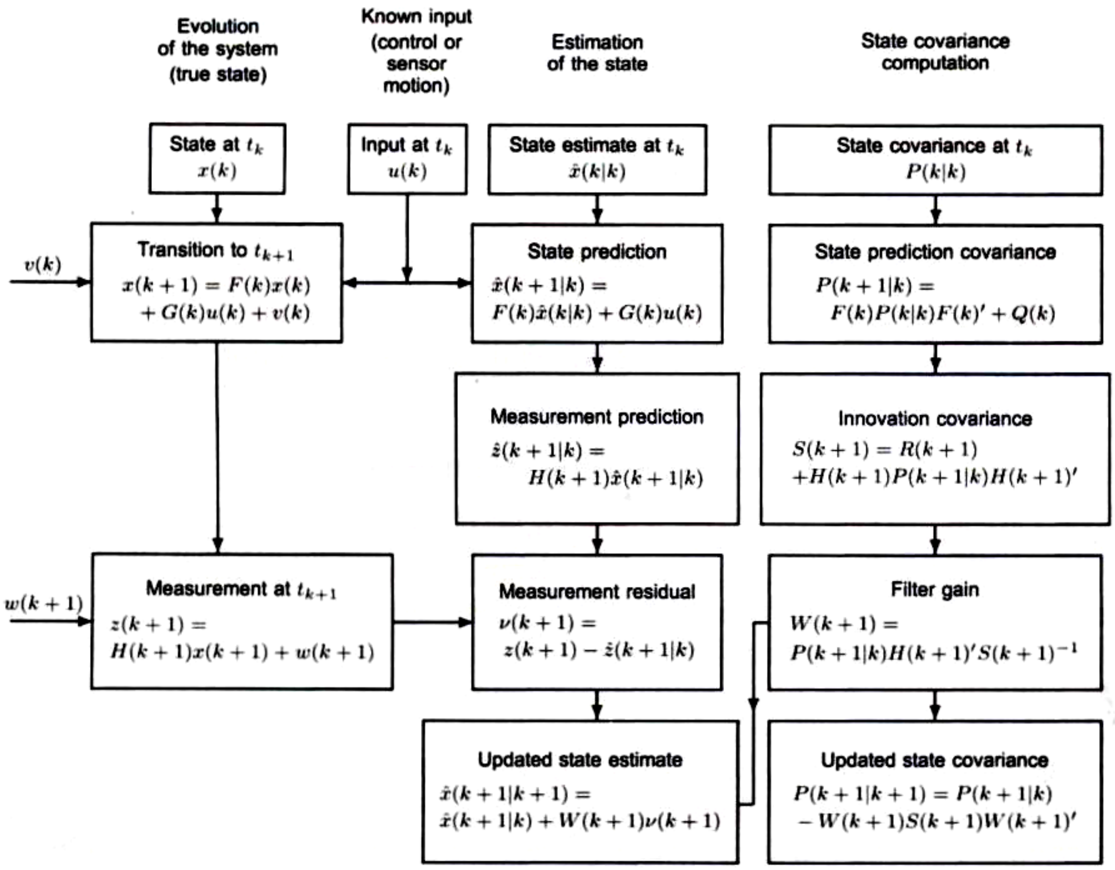

Figure 4: Block diagram of Kalman filter

Consistency for the Kalman filter is defined as the accuracy of the assumed dynamic model. In case of lack of accuracy, the Kalman filter model does not provide a correct estimate of the state vector of the system. If the system model is accurate and the linear normal assumption applies, the conditional distribution x(k) is as follows.

$$p[x(k) \mid Z^k] = N[x(k); \hat{x}(k,k), P(k,k)] \quad (10)$$

The system model includes the dynamic equation of the system, the measurement equation, and the statistical characteristics of the noises appearing in the equations. If all parameters are accurately modeled, Equation (11) is completely accurate. However, the purpose of consistency discussion is to know to what extent the assumed model is acceptable.
The Kalman filter consistency test is based on the fact that under the assumption of linear normality, the normalized error of estimate square (NEES) follows a Chi-squared distribution with n_x degrees of freedom. Therefore, we have:

$$E[\tilde{x}(k,k)'P(k,k)^{-1}\tilde{x}(k,k)] = n_x \quad (11)$$

The initial configuration plays a vital role in the Kalman filter. The initial covariance matrix should reflect the amount of error in the initial state vector without bias. Otherwise, the Kalman filter does not give the correct weight to the initial values in estimating the parameters. For example, if the initial value is not very accurate and the initial covariance matrix is very small, the filter assigns more weight to the initial value and the effect of this inaccurate initial value remains for a long time. This may lead to filter divergence.

1. Modeling the kinematic equations of motion

Due to the discrete nature of observations in phased array radars, it is necessary to model the equations of motion discretely in time. Commonly used models are constant velocity and constant acceleration models. In the constant velocity model, the movement acceleration is modeled as a white random process. However, in the constant acceleration model, the rate of change of acceleration (Jerk) is assumed to be a white process. In this model, the movement

acceleration follows a Wiener process. One of the important points in the implementation of tracking systems is the dynamic model selected for the targets. For example, tracking a ballistic missile requires its dynamic models, which are different from satellite dynamic models. Fighter planes with very high maneuverability require different dynamic models from larger planes (for example, cargo or passenger planes). Commercial and passenger airplanes generally require simpler models due to very little maneuverability [7, 8].
Most of the extended models, especially 2D and 3D models, are suitable for aircraft, although they can be used for many other purposes. Many such aircraft models are accurate, but most clearly ignore the effects of wind. There are a significant number of dynamic models for ballistic targets (such as ballistic missiles) and they are reviewed in [9]. The studies conducted in [9, 10] show that few dynamic models have been proposed for applications such as submarines, ships, and land targets.

The constant velocity model is a second-order model which is expressed by the following relation.

$$\mathbf{x}(k+1) = \mathbf{F}\mathbf{x}(k) + \mathbf{\Gamma} v(k) \tag{12}$$

where F is the transition matrix of the system state, which is compiled as follows.

$$\boldsymbol{F} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \tag{13}$$

where T is a vector of size n_x as noise gain. Also, the scalar v(k) is a white sequence with zero mean and variance σ_v^2 according to the following relation.

$$E[v(k)v(j)] = \delta_{kj}\sigma_v^2 \tag{14}$$

According to the last equations, in the second-order model with constant velocity, the target suffers a constant acceleration in each sampling interval. This acceleration is assumed to be independent from one interval to another.
The constant acceleration model is defined similarly to the constant velocity model in Equation (14). In this model, v(k) represents the acceleration change rate (Jerk). The state transfer and noise gain matrices for this model are compiled as follows.

$$\boldsymbol{F} = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

and

$$\boldsymbol{\Gamma} = \begin{bmatrix} T^2/2 \\ T \\ 1 \end{bmatrix} \tag{16}$$

The variance matrix Q is calculated as follows.

$$\boldsymbol{Q} = \boldsymbol{\Gamma}\sigma_v^2\boldsymbol{\Gamma}' = \begin{bmatrix} T^4/4 & T^3/2 & T^2/2 \\ T^3/2 & T^2 & T \\ T^2/2 & T & 1 \end{bmatrix}\sigma_v^2 \tag{17}$$

2. Extended Kalman Filter

The EKF filter is obtained based on the linearization of *f* and *h* functions around the last estimation point. Linearization of Equation (20) leads to the following relation.

$$\boldsymbol{x}(k+1) = f[k,\hat{\boldsymbol{x}}(k,k)] + \boldsymbol{f}_x(k)[\boldsymbol{x}(k) - \hat{\boldsymbol{x}}(k,k)] + \boldsymbol{HOT} + \boldsymbol{v}(k) \tag{18}$$

where $\boldsymbol{f}_x(k)$ is the Jacobian of vector *f* calculated at the last estimation point.
Also, HOT is an abbreviation for higher-order terms. Jacobian vector f is obtained according to the following relation.

$$\boldsymbol{f}_x(k) \triangleq [\nabla_x \boldsymbol{f}(k,x)']'\big|_{x=\hat{x}(k,k)} \triangleq \partial \mathbf{f}/\partial \mathbf{x} \tag{19}$$

By taking the conditional mean from Equation (4-66) and removing the high-order terms (HOT), the next state is calculated.

$$\hat{\boldsymbol{x}}(k+1,k) = \boldsymbol{f}[k,\hat{\boldsymbol{x}}(k,k)] \quad (20)$$

The residual vector (error vector) is calculated from the difference of Equations (3-66) and (3-68).

$$\tilde{\boldsymbol{x}}(k+1,k) = \boldsymbol{f}_x(k)\tilde{\boldsymbol{x}}(k,k) + \boldsymbol{HOT} + \boldsymbol{v}(k) \quad (21)$$

The prediction covariance matrix is calculated from the above relation as follows.

$$\boldsymbol{P}(k+1,k) = E[\tilde{\boldsymbol{x}}(k+1,k)\tilde{\boldsymbol{x}}(k+1,k)'] = \boldsymbol{f}_x(k)\boldsymbol{P}(k,k)\boldsymbol{f}_x(k)' + \boldsymbol{Q}(k) \quad (22)$$

where the high-order terms (HOT) are ignored.

Similarly, we convert Equation (21) into a linear equation around the last estimation point.

$$\boldsymbol{z}(k+1) = \boldsymbol{h}[k,\hat{\boldsymbol{x}}(k,k)] + \boldsymbol{h}_x(k)[\boldsymbol{x}(k) - \hat{\boldsymbol{x}}(k,k)] + \boldsymbol{HOT} + \boldsymbol{w}(k+1) \quad (23)$$

The prediction of the next observation for moment $k+1$ is obtained by using the conditional mean of the above relation and removing the high-order terms (HOT).

$$\hat{\boldsymbol{z}}(k+1) = E[\boldsymbol{z}(k+1)|\boldsymbol{Z}^k] = \boldsymbol{h}[k,\hat{\boldsymbol{x}}(k,k)] \quad (24)$$

The refresh vector can be calculated using the difference of Relations (23) and (24).

$$\boldsymbol{v}(k+1) = \boldsymbol{h}_x(k)\tilde{\boldsymbol{x}}(k,k) + \boldsymbol{HOT} + \boldsymbol{w}(k+1) \quad (25)$$

By ignoring the HOT term, the refresh covariance matrix is calculated as follows.

$$\boldsymbol{S}(k+1) = E[\boldsymbol{v}(k+1)\boldsymbol{v}(k+1)'] = \boldsymbol{h}_x(k)\boldsymbol{P}(k,k)\boldsymbol{h}_x(k)' + \boldsymbol{R}(k+1) \quad (26)$$

According to Relations (25), (26), the relations of the prediction covariance matrix and the refresh covariance matrix of the EKF filter are similar to the corresponding relations in the linear Kalman filter with a difference that the Jacobian matrices $\boldsymbol{f}_x(k)$ and $\boldsymbol{h}_x(k)$ play the role of the state transfer matrix and the measurement matrix, respectively.

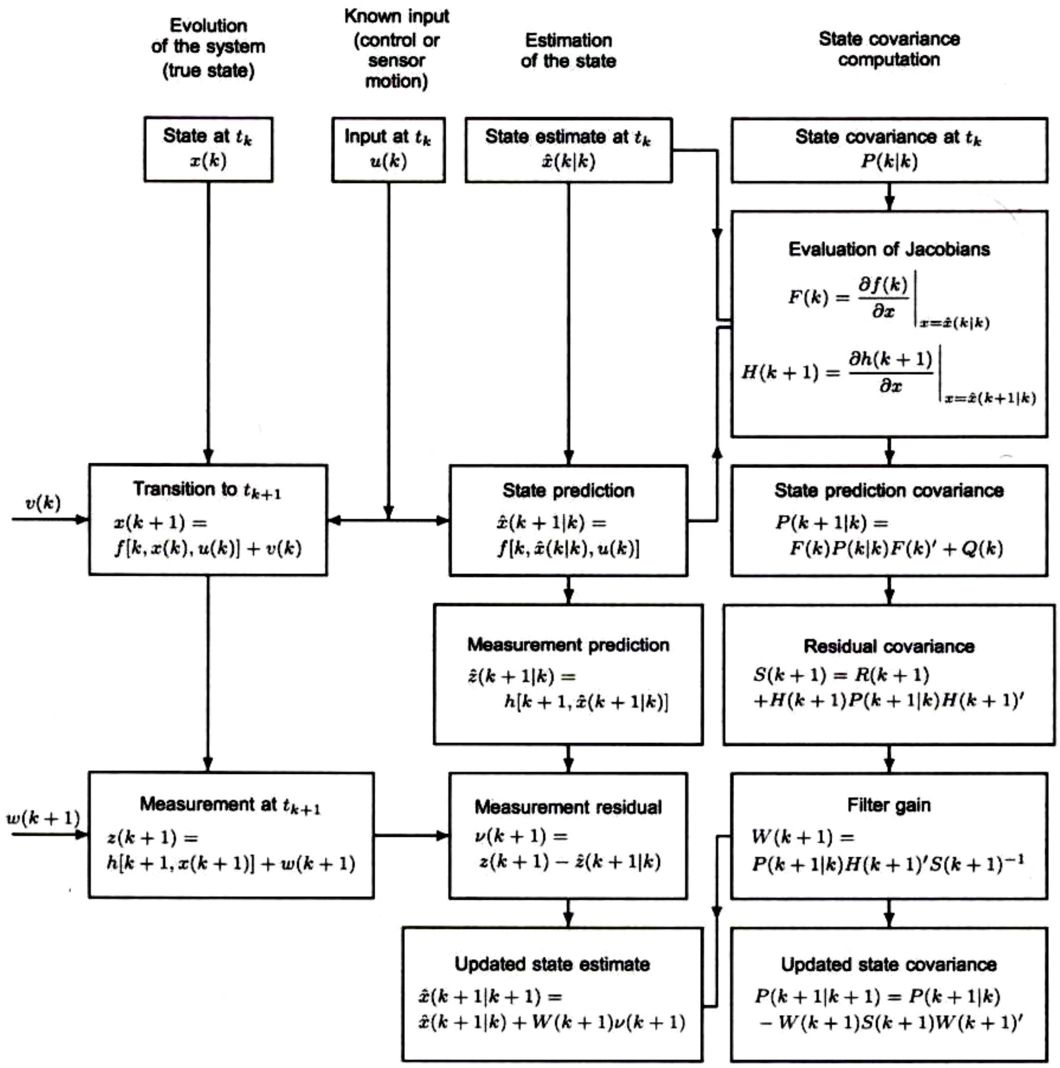

Figure 5: Extended Kalman filter (EKF) processing algorithm

3. Algorithm of interacting multiple models

In 1988, H.A.P.Blom and Y.Bar-Shalom [11] invented interacting multiple models (IMM) as the most effective method for estimating hybrid systems. A hybrid system is appropriately described by continuous values of the state space and a set of system states. State change or switching between different models is formed randomly. The optimal method for estimating hybrid systems is currently in theory and continuously increases exponentially with time, so it cannot be implemented in practice. Suppose that in the first step of estimating a hybrid system, the system can choose one of N specific models randomly. In the first step, we can create a suitable adaptation using N filters. In the second step, the system can switch to N other states. To have an optimal estimate, we must consider all the records. So, in the second step, the N^2 filters should be used due to the branching of each of the N models into N other models. In the same way, N^3 and N^4 filters should be applied for estimation in the third and fourth steps respectively. In [11], a scheduled cycle is introduced to adjust the exponential increase of the number of filters or hypotheses concerning time. As a result, only hypothesis N of the model is considered in each step [11 and 12].

According to Figure (6), the output of the whole system is equal to the weighted sum of the output of all filters. Each filter has a large or small effect on the output of the whole algorithm depending on the size f the corresponding weight. In simpler words, these weights can be converted into the probability of occurrence of the corresponding state in the hybrid system. The state corresponding to the larger weight at a particular moment indicates the possibility of

this state being dominant over the hybrid system at a particular moment. If the IMM algorithm is used to track the maneuvering target, the maneuvering target is the hybrid system itself, and the state variables of this system are the position and velocity of the target. During the maneuver, target acceleration is also added to other parameters as a state variable.
Therefore, the IMM algorithm can be implemented with two Kalman filters (a filter corresponding to constant acceleration dynamics and a filter corresponding to variable acceleration dynamics) to effectively track the maneuvering target. Figure (7) represents the IMM algorithm for *n* filters.

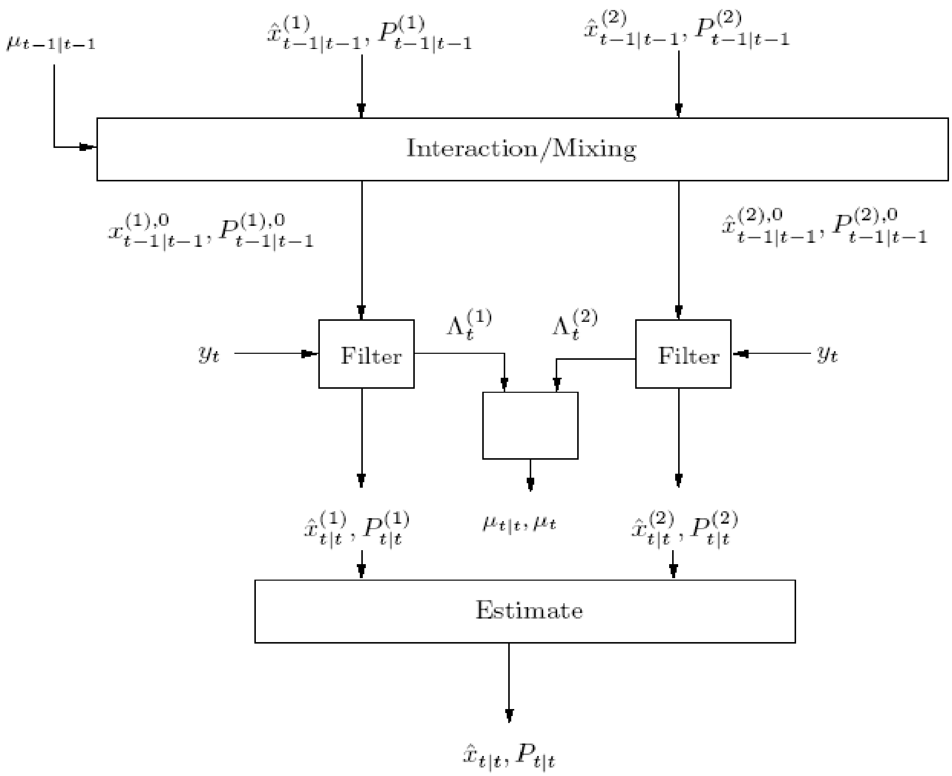

Figure 6: Schematic of IMM algorithm with two filters (two dynamic models)

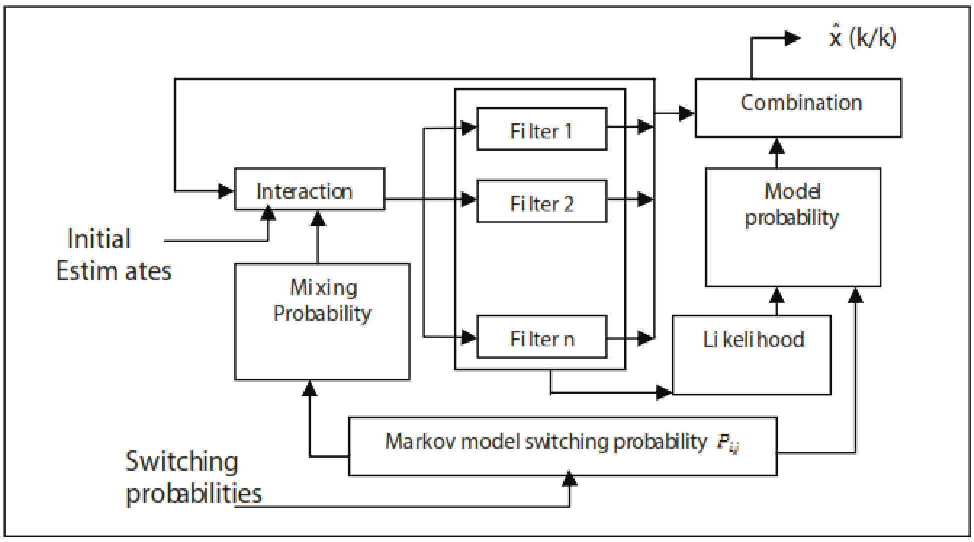

Figure 7: IMM algorithm for *n* filters

CONCLUSION

Today, advanced military systems are equipped with various sensors. In the case of unflawed and perfect sensor operation, target tracking can be done with simple geometry. In general, sensors are imperfect and their measurements are corrupted by noise. In addition, a single

sensor may not be able to provide all information about the target. For this reason, filters and multiple sensors are used to enhance target-tracking capabilities. Radar data can measure range with good resolution. Although radar data provides enough information for target tracking, angular measurements (horizontal and vertical angle) of radars are not very accurate. On the other hand, IRST sensor data can measure the horizontal and vertical angles with good resolution. Although IRST can show the direction of the target with very high accuracy, it cannot identify its location due to the lack of range measurement.
The IMM algorithm has several advantages, such as estimating the state of a dynamic system with several behavioral states, switching from one state to another, and a filter with variable bandwidth. This feature enables IMM to track maneuvering targets. In the algorithm, a good tradeoff between complexity and efficiency has been established. The computational load required for the algorithm is almost linear according to the size of the problem (that is, the number of models). At the same time, its efficiency is the same as algorithms with quadratic nonlinear complexity according to the number of models. For problems such as tracking, the interactive feature in the IMM algorithm is very useful. The reason is that this algorithm works almost the same as the Bayesian filter. IMM estimator is one of the most effective and simple methods for estimation in hybrid systems. As a result, it is suitable for tracking multi-target and multi-sensor systems. The IMM procedure is based on solid and stable principles, which is very suitable for the problems of tracking targets while maneuvering. It is also considered a recursive and modular algorithm that does not need additional circuits to register maneuvers.

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