A NUCLEAR PLUME DETECTION AND TRACKING MODEL FOR THE ADVANCED AIRBORNNE EARLY WARNING SURVEILLANCE AIRCRAFT

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Abstract: In this study, a new concept and means of nuclear plume detection and tracking (NPDT) for the advanced airborne surveillance aircraft is introduced. The method of nuclear plume detection for the advanced airborne early warning aircraft proposed here consists of three major components: 1) Detection and tracking of multiple targets by using a radar sensor and IFF sensor fusion tracker, such as the widely use Extended Kalman Tracker with Multi-sensor Track Fusion technology, 2) Use of a Knowledge Data Base to store air target characteristics, and 3) Use of Statistical Pattern Recognition technique with the Modified Bayesian Model to classify target tracks and identify the nuclear plume. The simulation and analysis is provided.

1. INTRODUCTION

In the war on terrorism, the greatest fear is the nuclear bomb and chemical or biological weapons of mass destruction. Up to now, there has been no method for an airborne early warning aircraft, operating at a long distance and high altitude, to detect and track the radiation plume from a nuclear detonation. The objective of this paper is to introduce a concept and means of nuclear plume detection and tracking (NPDT) for the advanced airborne surveillance aircraft. This idea is new and technological feasible. If we can detect and track the nuclear plume from aircraft 200 miles distant and flying at 30,000 feet, homeland security can inform command and control headquarters, and quickly advise civilians to take shelter from the coming radiation and thereby avoid mass destruction by radiation.

The best way to fight terrorism is to use advanced technology to attack the terrorists before they attack us. But, in case that is not totally successful, we should also prepare a means to detect and track the nuclear plume, in case the worst happens. Traditionally, the detection of radiation from a nuclear explosion is by using the Geiger counter. But this technology is only useful at a short distance. For radiation detection from long distance and high altitude, a new technology is needed.

The method of nuclear plume detection for the advanced airborne early warning aircraft proposed here consists of three major components:

1) Detection and tracking of multiple targets by using a radar sensor and IFF sensor fusion tracker, such as the widely used Extended Kalman Tracker with Multi-sensor Track Fusion technology.
2) Use of a Knowledge Data Base to store air target characteristics.
3) Use of Statistical Pattern Recognition with the Modified Bayesian Model to classify target tracks and identify the nuclear plume.

The Extended Kalman Tracker and Multi-Sensor Track Fusion Model, the Knowledge Database and the Statistical Pattern Recognition technique will be implemented in the software chips installed in the mission computers on board the advanced airborne early warning surveillance aircraft.

The authors will explain how multiple target detection and tracking works, the mathematical algorithms supporting the method, and how that technology can become daily routine by the airborne early warning surveillance aircraft for homeland security. We will also explain how the nuclear plume can be discriminated from other airborne targets such as aircraft, birds, and natural clouds of weather. We can only use simulated data to demonstrate how the nuclear plume detection for the advanced airborne early warning aircraft works. The presentation will include data screens showing the real-time multiple target tracking as it might look on the surveillance aircraft and also demonstrate the nuclear plume detection and tracking with simulated data.

2. THE ARCHITECTURE OF THE NPDT MODEL

Figure 1 shows the architecture of the NPDT model. The function of each block in this architecture will be explained in detail in the following sections.

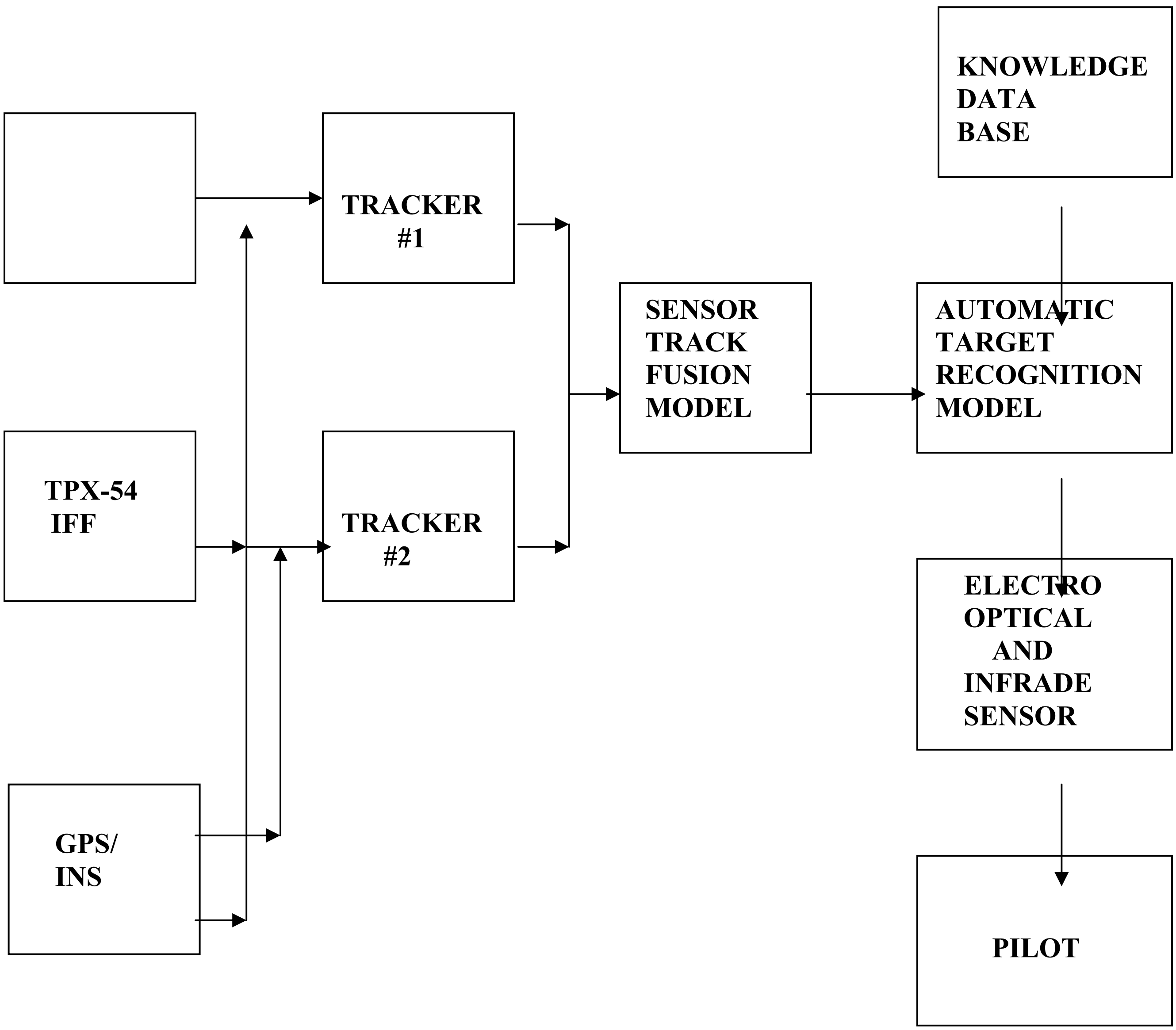


Figure 1. The architecture of the NPDT model.

2.1 THE RADAR SENSOR

The airborne early warning aircraft must be equipped with a search radar to detect multiple air targets in the vicinity of the aircraft at a long range. The radar must include a preprocessor to provide processed target reports. Target reports must include azimuth, elevation, range, and range-rate of the targets. These reports will be processed by NPDT in real-time.

2.2 THE IFF SENSOR

The Identification Friend or Foe (IFF) subsystem must be able to interrogate all targets in the area to provide position, mode code, and altitude. It must have a directional transmit/receive antenna slaved to the search radar antenna to interrogate the same targets the radar is reporting. The sensor fusion technology described below will actually make the determination of which target reports are from the same aircraft. But by moving the IFF antenna in synchronization with the radar antenna, it insures that both sensors report the target whenever possible.

2.3 THE GPS/INS

Any traditional Inertial Navigation System (INS) can provide ownship position and attitude to the NPDT mission system. Modern INS systems usually also include Global Positioning System (GPS) as a background reference. In this way, GPS positioning is available for normal INS startup alignment and continued in-flight verification of alignment.

The GPS/INS must provide ownship latitude, longitude, course, speed, and acceleration. This information will be used by the NPDT in real-time to translate radar and IFF target reports into ground stabilized position, velocity, and acceleration. This is needed by the NPDT for real-time sensor fusion.

2.4 THE ELECTROL OPTICAL SENSOR

An electro-optical and infrared turret mounted camera system will provide additional tactical identification capability to the airborne early warning aircraft pilot. The NPDT system would be designed to automatically direct the camera to any detected nuclear plume thus giving the pilot an immediate visual and infrared view of the event.

2.5 THE EXTENDED KALMAN TRACKER

The extended Kalman Tracker is a widely used tracker for radar. It can be found in any advanced Airborne Early Warning Surveillance aircraft, GPS, and Missiles. The Extended Kalman Tracker is very accurate if the radar sensor can provide accurate target reports.

The Extended Kalman Tracker expects an input vector extracted from a radar report by pre-signal processing. The input vector generally contains target elements such as range, range rate, azimuth angle and elevation angle. Radar reports generally provide very accurate target information. The output vector generated by the Extended Kalman Tracker contains very accurate target information, such as three dimensional target position, velocity, and acceleration.

The mathematical algorithm for the Extended Kalman Tracker can be expressed as the following equations:

(1) Propagating Target State Vector:

$$X_k = \phi * X_{k-1} + U$$

(2) Propagating Target State Covariance Matrix:

$$P_k = \phi * P_{k-1} * \phi^T + Q$$

(3) Kalman Gain Matrix:

$$K = P_k * H^T * INV\{ H * P_k * H^T + R \}$$

(4) Gating (CHI-SQ TEST):

$$G(Z) = (Z - H * X_k)^T * INV\{S\} * (Z - H * X_k)$$

Where $S = \{ H * P_k * H^T + R \}$

(5) Update Target State Covariance Matrix:

$$P_{k+1} = (I - G * H) * P_k$$

(6) Update Target State Vector:

$$X_{k+1} = X_k + G * (Z - H * X_k)$$

Where:

X_k is the Target State Vector at time k

P_k is the Target State Covariance Matrix

G is the Kalman Gain Matrix

Z is the Measure Vector

ϕ is the Target Transition Matrix

I is the Identity Matrix

H is the Jacobian Matrix

2.6 IFF TRACKER

This is a digital IFF tracker, which is different from the traditional IFF Sensor detector base on a Receiver and Transmitter using two separate radio frequencies - one for asking the approaching target to identify itself, and another frequency for the approaching target to respond to the request.

The digital IFF tracker requires IFF Sensor reports as input vector, which are extracted by pre-signal processing. The input vector contains target azimuth angle, and range. The output vector from the IFF Tracker is similar to the radar tracker and contains very accurate target information, such as three dimensional target position vectors, velocity vector and acceleration vector.

The mathematical algorithm for the IFF tracker is similar to the existent moving target tracker. An output vector is converted from a three dimensional position vector, velocity vector and acceleration vector.

The following parameters are the elements of the IFF tracker:

(1) Latitude.
(2) Longitude.
(3) Bearing.
(4) Range.
(5) Range Rate.
(6) Ground Speed.
(7) Course.
(8) Altitude.

All above parameters can be defined mathematically as following:

(1) Latitude(φ):

Given R_x , R_y and R_z

Where $R_x = R*\cos(EL)*\cos(AZ)$.
$R_y = R*\cos(EL)*\sin(AZ)$.
$R_z = R*\sin(EL)$.
R = Range of a given target.
EL = Elevation angle.
AZ = Azimuth angle.

The geocentric Latitude(φ) can be found as following:

$$\varphi' = \mathrm{atan}\{ R_z / \mathrm{sqrt}(R_x^2 + R_y^2) \}$$

and $\tan(\varphi) = \tan(\varphi') / \{ 1.0 - f^2 \}$

f =flattening factor given by the earth model = 0.003367.

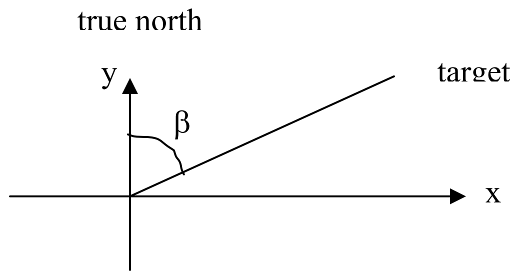
$\varphi = \mathrm{atan}[\tan(\varphi') / \{ 1.0 - f^2 \}]$ is defined as the geodetic latitude.

(2) Longitude(θ):

$\theta = \mathrm{atan}\{ R_x / R_y \}$ is defined as the geodetic Longitude.

(3) Bearing(β):

$\beta = \text{atan}\,(x/y)$



(4) Range (R):

$R = \text{sqrt}\{\, x^2 + y^2 + z^2 \,).$

(5) Range Rate (R') :

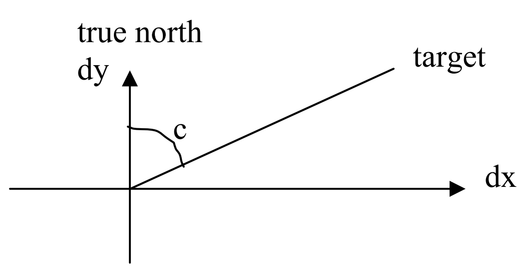
$R' = \{\, x * dx + y * dy + z * dz \,\} / R$

(6) Ground Speed(GS)

$GS = \text{SQRT}\{\, dx^2 + dy^2 \,\}$

(7) Course (C) or direction:

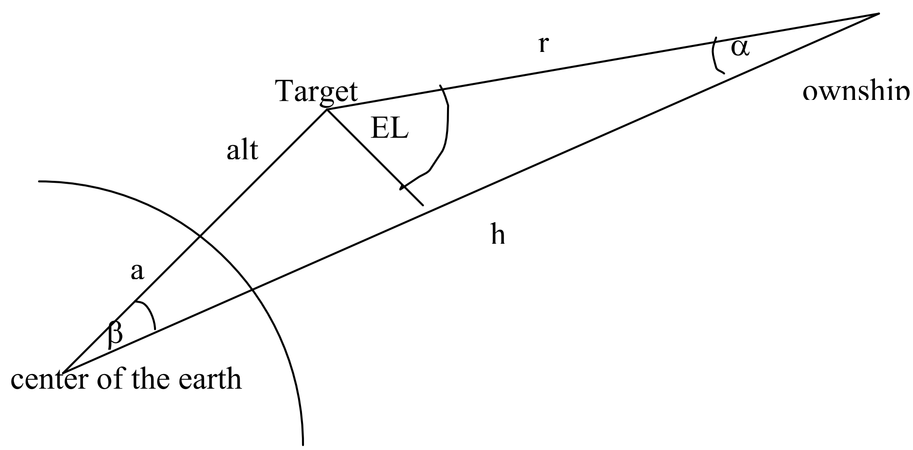
$C = \text{atan}\ \{\, dx / dy \}.$



(8) Altitude (alt):

$$\text{Alt} = \sin[\, 90.0 - \{\, \text{asin}\, [\, r * \cos(EL) / (a+h)] + EL \} \,] * [\, (a+h) / \cos(EL) \,] - a \quad \text{------(A)}$$

Where r = range between ownship P-3 and the target.
h = altitude of the ownship P-3.
a = radius of the earth.



Apply the law of sin:

$(a + alt)/ \sin(\alpha) = r / \sin(\beta) = (a + h) / \sin(90 + EL)$ ----------------------------(B)

from the triangle, we have:

$$\alpha + \beta + (90 + EL) = 180.0$$

that is $\alpha + \beta + EL = 90.0$ ---(C)

and $\sin(90 + EL) = \cos(EL)$ --(D)

r, h, and EL are the output parameters of the tracker, therefore the unknown parameter “alt” as expressed in (A), can be found by solving equations (B), (C) and (D).

The normal input vector from radar to the tracker is range, range rate, elevation angle and azimuth angle or target position , velocity and acceleration vectors.

3. MULT-SENSOR TRACK FUSION MODEL

The objective of the Multi-Sensor Track Fusion Model (MSTFM) is to generate the fused track from the radar tracker and IFF tracker. The fused track is the integrated target track from the radar and IFF track and it is the best of the radar and IFF track.

The Multi-Sensor Track Fusion Model consists of radar sensor, IFF sensor, and GPS/INS sensor, Extended Kalman Tracker, Multi-Sensor Correlation processor, and Pilot Vehicle Interface Unit.

The block diagram of the Multi-Sensor Track Fusion Model can be represented as the following shown in Figure 2.

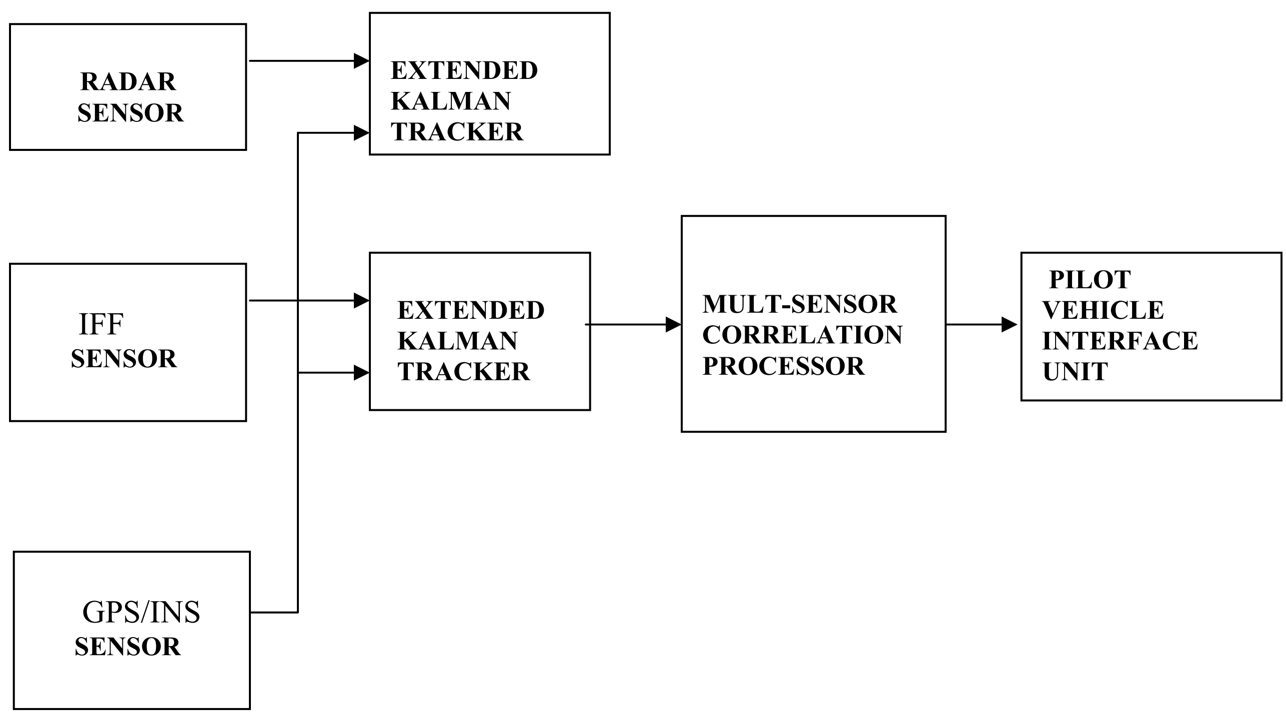


Figure 2. The mutli-sensor track fusion model.

4. MULT-SENSOR CORRELATION PROCESSOR

The Objective of the Multi-Sensor Correlation Processor (MSCP) is to estimate the relationship between target state vectors X and Y. Suppose that one target state vector X is detected by radar sensor and the other target state vector Y is detected by IFF sensor. The Multi-Sensor Correlation Processor will calculate the correlation coefficient between target state vector X and target state vector Y. If the correlation coefficient between X and Y is one, then the target X and target Y can be identified as the same target. IF the correlation coefficient between target X and target Y is zero, one can conclude that target X and target Y are different types of target.

Mathematically, the correlation coefficient between target X and target Y can be expressed as follows:

$R_{xy} = X \bullet Y / (X\bullet X - X\bullet Y + Y\bullet Y)$

Where :

$X = \{ x1, x2, x3, \ldots\ldots\ldots\ldots xk)$

$Y = \{ y1, y2, y3, \ldots\ldots\ldots\ldots yk)$

$X\bullet X = SUM\{ xi \bullet xi\}$

$X\bullet Y = SUM\{ xi \bullet yi\}$

$Y\bullet Y = SUM\{ yi \bullet yi\}$

The Multi-Sensor Correlation Processor is the major component of the Multi-Sensor Track Fusion Model. There are many forms of multi-sensor correlation processor. The authors considered this one to be the easiest to apply multi-sensor correlation processor.

5. STATISTICAL PATTERN RECOGNITION MODEL (SPR)

How can one discriminate a nuclear plume from an unknown air target? This is a typical statistical pattern recognition problem and the object identity can be found by applying the Bayesian probability model.

Let:

$T = \{x_1, x_2, x_3, \ldots, x_n\}$ be the feature vector of an unknown object.

$C_k = \{x_1, x_2, x_3, \ldots, x_n\}$ be the feature vector of k-th object in the Knowledge Data Base.

Then, the Bayesian probability model can be expressed as follows:

$$\rho(\boldsymbol{C}_k / T) = \rho(T / \boldsymbol{C}_k)\, \rho(\mathbf{C}_k) / \Sigma_i \rho(T / \mathbf{C}_i)\, \rho(\boldsymbol{C}_i); \quad i = 1, 2, 3, ..., n \qquad (2)$$

Where:

$\rho(\boldsymbol{C}_k/T)$ is the probability of the unknown object T identified as the k-th object in the Knowledge Database.
$\rho(\boldsymbol{C}_k)$ is the probability of the k-th object in the Knowledge Database.
$\rho(T/\boldsymbol{C}_\mathbf{i})$ is the conditional probability of the unknown object T given the i-th object is present in the Knowledge Database.
$\rho\ (T / \boldsymbol{C}_i) = K \exp 0.5(T - C_\mathbf{i})^t \Sigma_i^{-1}(T - \boldsymbol{C}_i)$; i = 1, 2, 3, …, n

where:

$K = 1 / n \sqrt{\Sigma_i}$

$$\Sigma_\mathrm{i} = \begin{vmatrix} \delta^2_{x_1} & & 0 \\ & \delta^2_{x_2} & \\ 0 & & \delta^2_{x_n} \end{vmatrix} \text{ is the covariance matrix.}$$

Σ_i^{-1} = the inverse of the covariance matrix.

Properties:

(1) $0 \leq \rho(C_i/T) \leq 1$ for i = 1, 2, 3, …, n
(2) $\Sigma_\mathrm{I}\, \rho(C_i / T) = 1$

Decisions made by the Bayesian Model:

(1) The unknown object, characterize d by T, can be identified as the k-th object in the Knowledge Database when $\rho(C_k/T) \geq \rho(C_i/T)$; for all i =1, 2, 3, …, n
(2) The unknown object, characterized by T, cannot be identified as the k-th object in the Knowledge Database when $\rho(C_k/T) < \rho(C_i/T)$; for all i = 1, 2, 3, …, n

The Bayesian Model requires multi-normality distribution assumption and equal probability of detection on each class and null sets between classes. In the real world, these assumptions may not be true. In that case, the Bayesian Model may not be suitable to solve real world problems. Therefore the Bayesian Model needs some kind of modification before it can be applied to real world problems[3].

The Modified Bayesian Model can be expressed mathematically as following:

$$D_i(T) = (T - C_i)^{-1} \Sigma_\mathrm{i}^{-1} (T - C_i);\ i = 1, 2, 3, ..., n$$

Decisions made by the Modified Bayesian Model:

If $D_\mathrm{k}(\mathrm{T}) = \min D_i(T)$; i = 1, 2, 3, ..., n

Then the unknown object, characterized by T, can be identified as the k-th object in the Knowledge Database, otherwise the unknown object cannot be identified with any object in the Knowledge Database.

6. THE KNOWLEDGE DATA BASE(KDB)

There are three questions that the authors want to address in this section:

(1) What is the Knowledge Database (KDB)?
(2) Why we need the Knowledge Database?
(3) How to create a knowledge Database?

Any database containing true information about target parameters can be defined as the Knowledge Database. For example, in our particular database, there are two distinct types of target parameters, one is air target characteristics and the other is nuclear plume characteristics. In this database, each target parameter contains a target state vector with elements such as Latitude, Longitude, Range, Range-Rate, Bearing, Velocity, Course or direction, altitude and Minimum Detection Yield. All the information characterizes the air targets and nuclear plume. Therefore we call this database the Knowledge Database.

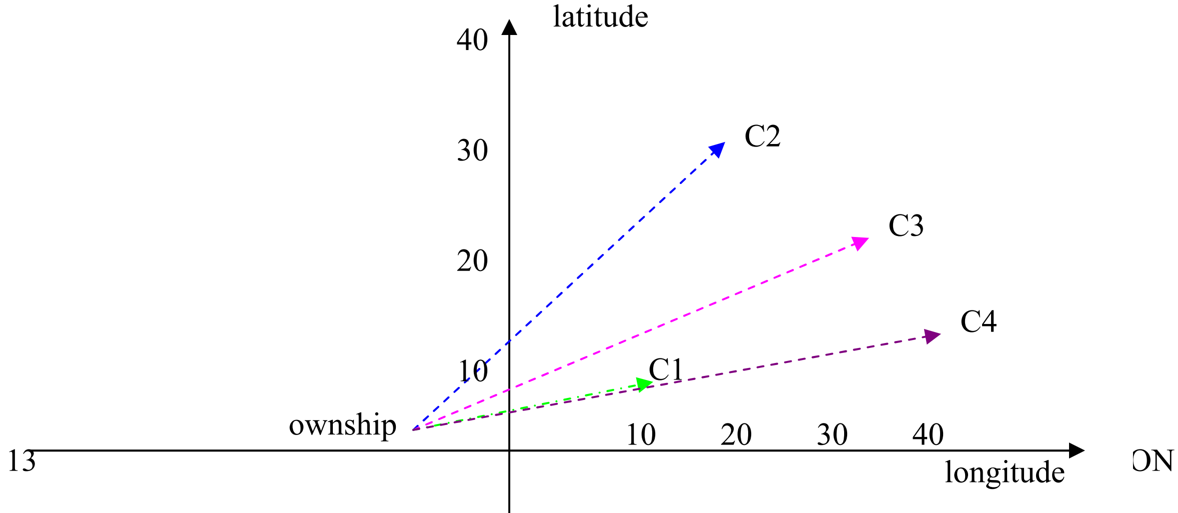
The Knowledge Database plays a very important role in the detection and tracking of a nuclear plume by the Airborne Early Warning Aircraft. After detection and tracking of air target, we have to discriminate the air target between general aircraft and a nuclear plume. In that process, the Statistical Pattern Recognition Model is needed to calculate the geometrical distance between each aircraft from the unknown nuclear plume. The geometrical distance is a function of two state vectors, one from the Extended Kalman Tracker and the other one from the Knowledge Database. Therefore, the Knowledge Database provides true target information to discriminate the aircraft from the nuclear plume.

Every Knowledge Data Base is different, therefore each creation is different. We use the real time flight test data, and randomly select four distinct targets for our simulation. They are here denoted by T1, T2, T3 and T4. In this example :

T1 = {5.0 , 10.0, 75.0, 60.0, ,150.0,75.0,20.0}
T2 = {30.0, 20.0, 35.0, 80.0, 2.0, 200.0,35.0, 40.0}
T3 = {20.0,30.0, 60.0, 70.0, 2.0, 100.0, 60.0,30.0}
T4 = {10.0, 40.0,85.0, 65.0, 2.0,140.0,85.0,25.0}

We purposely replace the parameter of range-rate by the new parameter –Minimum Detectible Yield (MDY) which is a function of nuclear isotopes and is the characteristic of the nuclear plume. The nuclear plume for T1 =1.0, T2=0, T3=0, T4=0. That means only T1 is the true nuclear plume, and T2, T3 and T4 are all aircraft.

Minimum detectable yield is a concept developed to estimate the size of nuclear detonation back at the time China was doing underground nuclear tests. Refer to references 8 and 9.



7. SIMULATION & ANALYSIS

The radar tracker, IFF tracker, and Multi-Sensor Track Fusion models were verified by mathematical target modeling in the laboratory. The models were then tested with real time flight test data. Refer to radar track, IFF track, and Fused Track displays in the following section. These displays demonstrated the detection and tracking of air targets in the real time environment.

In the first stage, the trackers and fusion models are verified. After the air targets are accurately detected and tracked, then it is necessary to discriminate what has been detected and tracked. Statistical Pattern Recognition Model and Knowledge Database play an important role in this stage.

For example: four randomly picked air targets are used to demonstrate the discrimination between air targets and nuclear plume. The air targets all have state vector as follows. Note the insertion of Minimum Detectible Yield (MDY).

Target State Vector = {Lat, Lon, Range, Bearing, MDY, Ground-Speed, Course, alt}

The four air targets are represented by the following numerical value:

T1 = {5.0, 10.0, 75.0, 60.0, 1.0, 150.0, 75.0, 20.0}
T2 = {30.0, 20.0, 35.0, 80.0, 0.0, 200.0, 35.0, 40.0}
T3 = {20.0, 30.0, 60.0, 70.0, 0.0, 100.0, 60.0, 30.0}
T4 ={10.0, 40.0, 85.0, 65.0, 0.0, 140.0, 85.0, 25.0}
MDY = 0.0 ---------- 0% of Radio-Isotope
MDY = 1.0 ----------100% of Radio-Isotope

T1 is the Nuclear Plume, T2, T3 and T4 are the general aircraft.
All of these target state vectors are stored in the Knowledge Database.

In the second stage, one unknown state vector is output from the Multi-Sensor Track Fusion Model, and one state vector is extracted from the Knowledge Database. Then the Statistical Pattern Recognition Model uses these two state vectors to calculate the Geometrical Distance. If the calculated Geometrical Distance is zero between the unknown state vector(X) and the state vector (Y) from the Knowledge Data Base, then X and Y are identified as the same target.

The following four simulated cases are used to demonstrate the discrimination of the nuclear plume from general air targets:

Case #1
Consider target T1 from the multi-sensor track fusion model in the first stage. The following target state vector represents T1:

$$T1 = \{5.0, 10.0, 75.0, 60.0, 1.0, 150.0, 75.0, 20.0\}$$

As an unknown target, it may be a nuclear plume or just another general air target. The Statistical Pattern Recognition Model takes all the target state vectors in the knowledge database and calculates the “geometrical distance” between the unknown target state vector (T1) and all the other target state vectors (T1, T2, T3 and T4). The “geometrical distance” can be denoted by D(T1), D(T2), D(T3), and D(T4).

Mathematically, the result can be expressed as:

$$D(T1) = 0.0$$
$$D(T2) = 7226.0$$
$$D(T3) = 3560.0$$
$$D(T4) = 476.0$$

Since D(T1) is zero, which is the geometric distance between the unknown state vector and the target state vector (T1) in the knowledge database, therefore one can concluded that the unknown target T1 is positively identified as a nuclear plume .

Case #2
Consider target T2 from the multi-sensor track fusion model in the first stage. The following target state vector represents T2:

$$T2 = \{30.0, 20.0, 35.0, 80.0, 0.0, 200.0, 35.0, 40.0\}$$

As an unknown target, T2, may be a nuclear plume or just another general air target. Now the statistical pattern recognition model takes all the target state vectors in the knowledge database, and calculates the “geometrical distance” between the unknown target state vector (T2) and all the other target state vectors (T1, T2, T3 and T4). The “geometrical distance” can be denoted by D(T1), D(T2), D(T3), and D(T4).

Mathematically, the result can be expressed in the following:

D(T1) = 722.0
D(T2) = 0.0
D(T3) = 2650.0
D(T4) = 9850.0

Since D(T2) is zero , therefore one can conclude that unknown target T2 is positively identified as a general air target.

Case #3
Consider target T3 from the multi-sensor track fusion model in the first stage. The following target state vector represents T3:

T3 = {20.0, 30.0, 60.0, 70.0, 0.0, 100.0, 60.0, 30.0}

As an unknown target, it may be a nuclear plume or just another general air target. Now the Statistical Pattern Recognition Model takes all the target state vectors in the knowledge database, and calculates the "geometrical distance" between the unknown target state vector (T3) and all the other target state vectors (T1, T2, T3 and T4). The "geometrical distance" can be denoted by D(T1), D(T2), D(T3), and D(T4).

Mathematically, the result can be expressed in the following:

D(T1) = 3576.0
D(T2) = 2650.0
D(T3) = 0.0
D(T4) = 2300.0

Since the geometric distance between the unknown state vector and the target state vector (T3) in the Knowledge database is zero, therefore one can conclude that the unknown target T3 is positively identified as a general air target and is not a nuclear plume.

Case #4
Consider target T4 outputted from the multi-sensor track fusion model in the first stage. The following target state vector represents T4:

T4 ={10.0, 40.0, 85.0, 65.0, 0.0, 140.0, 85.0, 25.0}

As an unknown target, it may be a nuclear plume or just a general air target. Now the Statistical Pattern Recognition Model takes all the target state vectors in the knowledge database, and calculates the "geometrical distance" between the unknown target state vector (T4) and all the other target state vectors (T1, T2, T3 and T4). The "geometrical distance" can be denoted by D(T1), D(T2), D(T3), and D(T4).

Mathematically, the result can be expressed in the following:

$$D(T1) = 476.0$$
$$D(T2) = 9850.0$$
$$D(T3) = 2300.0$$
$$D(T4) = 0.0$$

Since D(T4) is zero, which is the geometric distance between the unknown state vector and the target state vector (T4) in the knowledge database, therefore one can conclude that unknown target T4 is positively identified as a general air target and is not a nuclear plume.

8. DISPLAY OF SENSOR TRACK FUSION MODEL

Figures 3 and 4 show some of the fused track results from Radar and IFF tracker. These fused information will provide the pilot integrated, real-time technical information which can be used for making decisions.

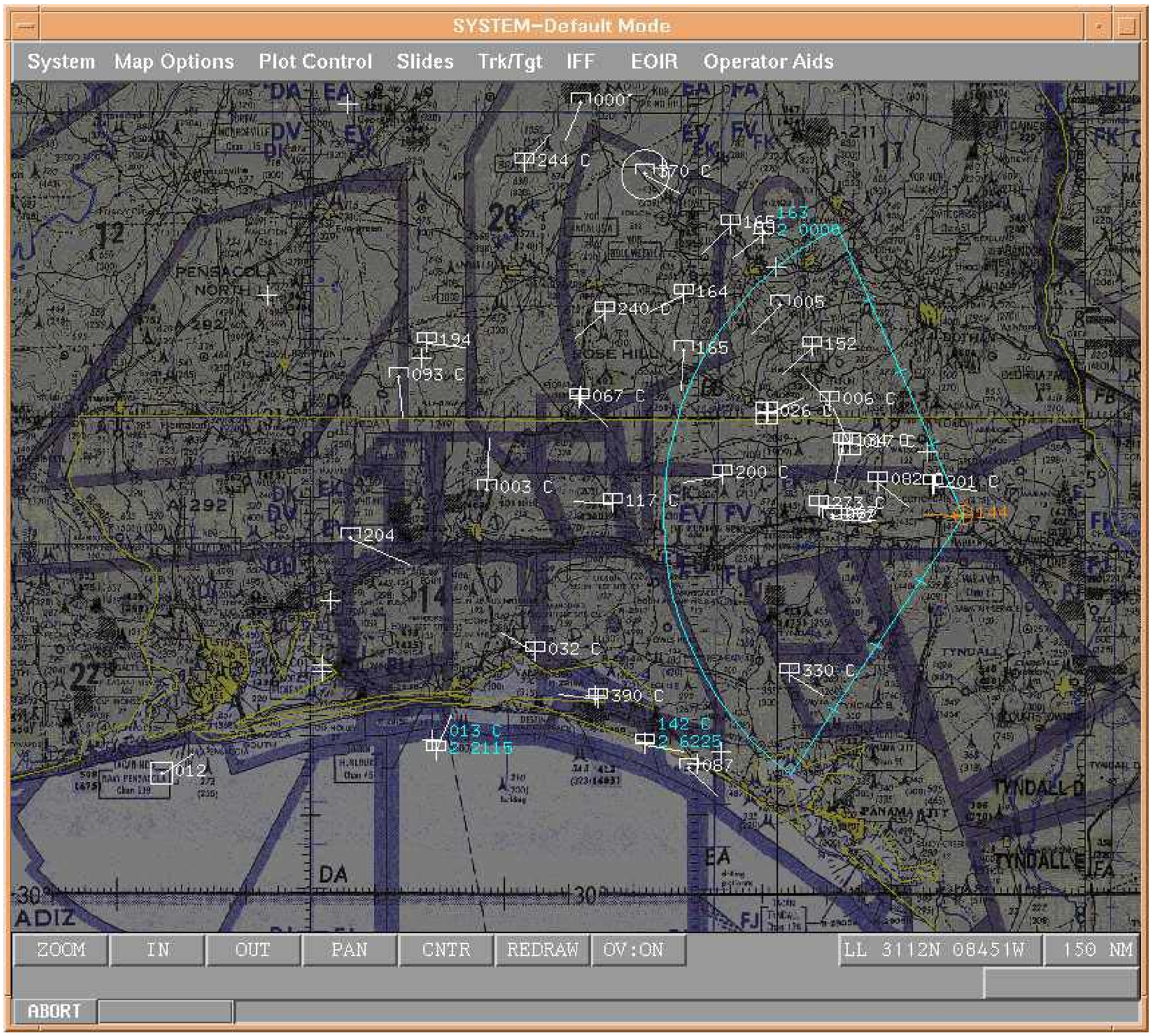


Figure 3. An example of fused IFF targets and radar targets.

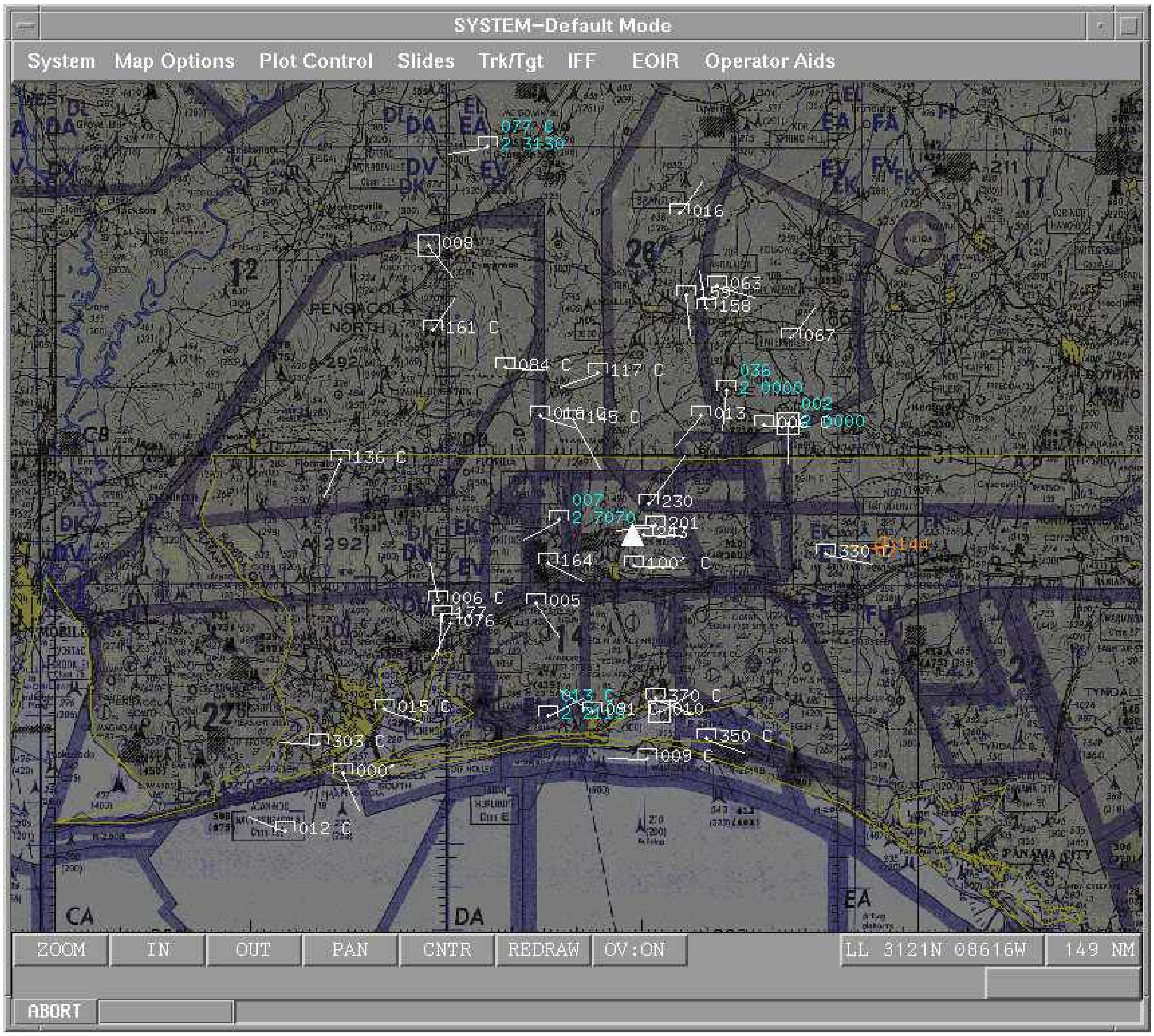


Figure 4. An example of hypothetical nuclear plume detection (the triangle symbol).

9. CONCLUSIONS

The new technology introduced in this paper, consists of three distinct concepts: (a) multiple target detection and tracking with IFF sensor, Radar Sensor and GPS/INS sensor, and Multi-Sensor Track Fusion; (b) discriminate nuclear plume from general air targets by using Statistical Pattern Recognition techniques with Knowledge Data Base; and (c) EO/IR sensor provides visual information to the pilot who will have the power to make the final decision.

The sensor track displays verified the concept of target detection and tracking and sensor track fusion. The four simulation cases verified the concept of nuclear plume discrimination. According to the International Monitoring System (IMS), the measurable characteristics of the nuclear plume is the Minimum Detectable Yield , which is a function of the Minimum detectable concentration of Xenon-135 and Barium-140. The release of these Radio isotope radionucleides during the nuclear explosion, makes the nuclear plume detection and tracking from the advanced surveillance aircraft at 200 nmiles and 40000 feet is feasible.

In the paper, the authors only offered a concept of detection and tracking a nuclear plume, and provided simulated information. There is no real time data to support our claims, because nuclear explosions are a rare event, no one wants to see it happen. More research work should be concentrated on how the characteristics of the nuclear plume are measured in addition to the feature vector with elements such as latitude, longitude, range, range-rate, bearing, MDY, ground speed and altitude. New parameters such as temperature, and size of the plume should be included. The new feature vector for the nuclear plume may enhance the detection and tracking of the nuclear plume.

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