A New Multi-Sensor Track Fusion Architecture for Multi-Sensor Information Integration

By

Dr. Buddy H Jean and John Younker**
Lockheed Martin Aeronautical Systems Company
Marietta, Georgia 30063

Dr. Chih-Cheng Hung
Southern Polytechnic State University
Marietta, Georgia

**** POC:770-494-8508/ FAX 770-494-9333**
buddy.h.jeun@lmco.com

ABSTRACT

This paper proposes a new multi-sensor track fusion model. The widely used multi-sensor track fusion model is based on the Extended Kalman Tracker whereas the new fusion model is based on the alpha beta gamma tracker. This new technology will integrate multi-sensor information and extract integrated multi-sensor information to detect, track and identify multiple targets at any time, in any place under all weather conditions. This technology can be applied to the development of fighter aircraft and also to the development of aircraft for Command, Control, Communication and Computer and Information, Surveillance and Reconnaissance (C4ISR). This technology will help to protect our Homeland and finally control and destroy any enemy who dares to challenge us from the air, land or the sea.

The advantage of this new Multi-Sensor Track Fusion Model over the currently used Multi-Sensor Track Fusion Model is that it is mathematically simpler. The algorithm needs no matrix inversion and no matrix element divide-by-zero. This means it is easier to implement and there will be no mid-air computer shut down or system crash. The architecture of the new Multi-Sensor Track Fusion Model includes Multi-Sensors such as radar, electronic warfare, the digital signal processor, the alpha beta gamma tracker, the multi-sensor correlation processor, the vehicle interface unit, and the flight crew.

The ultimate goal of this new Multi-Sensor Track Fusion Model is to generate fused tracks from all sensor trackers, and integrate all sensor information to provide the pilot and the C4ISR headquarters with time critical target information. Finally this new integration will help establish the air, land and sea superiority on the battlefield.

INTRODUCTION

A new multi-sensor track fusion model for fusing multi-sensor information in the integrated environment was inspired by the following:

(1) One of the most advanced new fighter aircraft is being designed to be the best air-to-air fighter. Every action is controlled by computer. There are three major sensors on board the aircraft: Radar, Electronics Warfare (EW), and Communication, Navigation, and Identification (CNI). The pilot only needs one of these sensors to fly the aircraft. Two of the three sensors can malfunction in the battlefield. During test flights pilots fly the aircraft with one sensor at a time and everything works perfectly. However, if the pilot wants to fly the aircraft with all three sensors, the only thing he has to do is throw the switch to integrate the three sensors. Hypothetically, if the on-board computer shuts down, this indicates that the integration of the on-board sensors is not working properly. This further implies that the multi-sensor information from these sensors is not properly fused.

(2) In the paper "A Multi-Sensor Fusion Track Solution to Address the Multi-Target Problem" [Jeun, Jayaraman], published by the 1999 National Symposium on Sensor and Data Fusion held at the John Hopkins University, the authors point out that one of the widely used multi-sensor fusion trackers is the Extended Kalman Tracker. In the close-in combat, tactical air reconnaissance, and surveillance environment, target track fusion becomes more complex. Processing target reports demands more computer power. But the algorithm of the extended kalman tracker involves matrix inversion, which slows down target processing.

The major components of new multi-sensor track fusion architecture consist of multiple sensors such as radar, EW, and CNI; a digital processor as feature selector; a global positioning system; alpha-beta-gamma tracker; multi-sensor correlation processor; pilot-vehicle interface unit; and pilot.

The basic operational principle is as follows. The Global Positioning System/ Inertia Navigation System provides the location and attitude of the aircraft. Multi-sensor processing provides the target reports containing azimuth angle, elevation angle, range, and range-rate of multiple targets. The Digital Signal Processor converts the target reports to target initial position, velocity, and acceleration. The Alpha-Beta-Gamma Tracker provides target tracks. The Drivers within the tracker provide the I/O operations for the tracker. The Multi-Sensor Correlation processor provides fused or integrated tracks. The Pilot Vehicle Interface Unit presents the integrated target information to the Pilot and C4ISR headquarters.

In the new sensor track fusion model for multi-sensor information integration, the tracker yields more than 99 percent accuracy for simulated target tracks. The multi-sensor correlation processor generates fused tracks with more than 98 percent accuracy. Based on the simulated target data, one can conclude that the new multi-sensor information integration model is superior to the current widely used integration model.

THE EXTENDED KALMAN TRACKER MODEL

Mathematically, the Extended Kalman Tracker model can be defined as follows:

A. Propagating state vector(U):

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

B. Propagating state covariance matrix(U):

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

C. Kalman gain matrix(U):

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

D. Gating algorithm(U):

$$G = (Z-H*X_k)^T * \{ H*P*H^T + R)^{-1} * (Z - H*X_k)$$

E. Updated state covariance matrix(U):

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

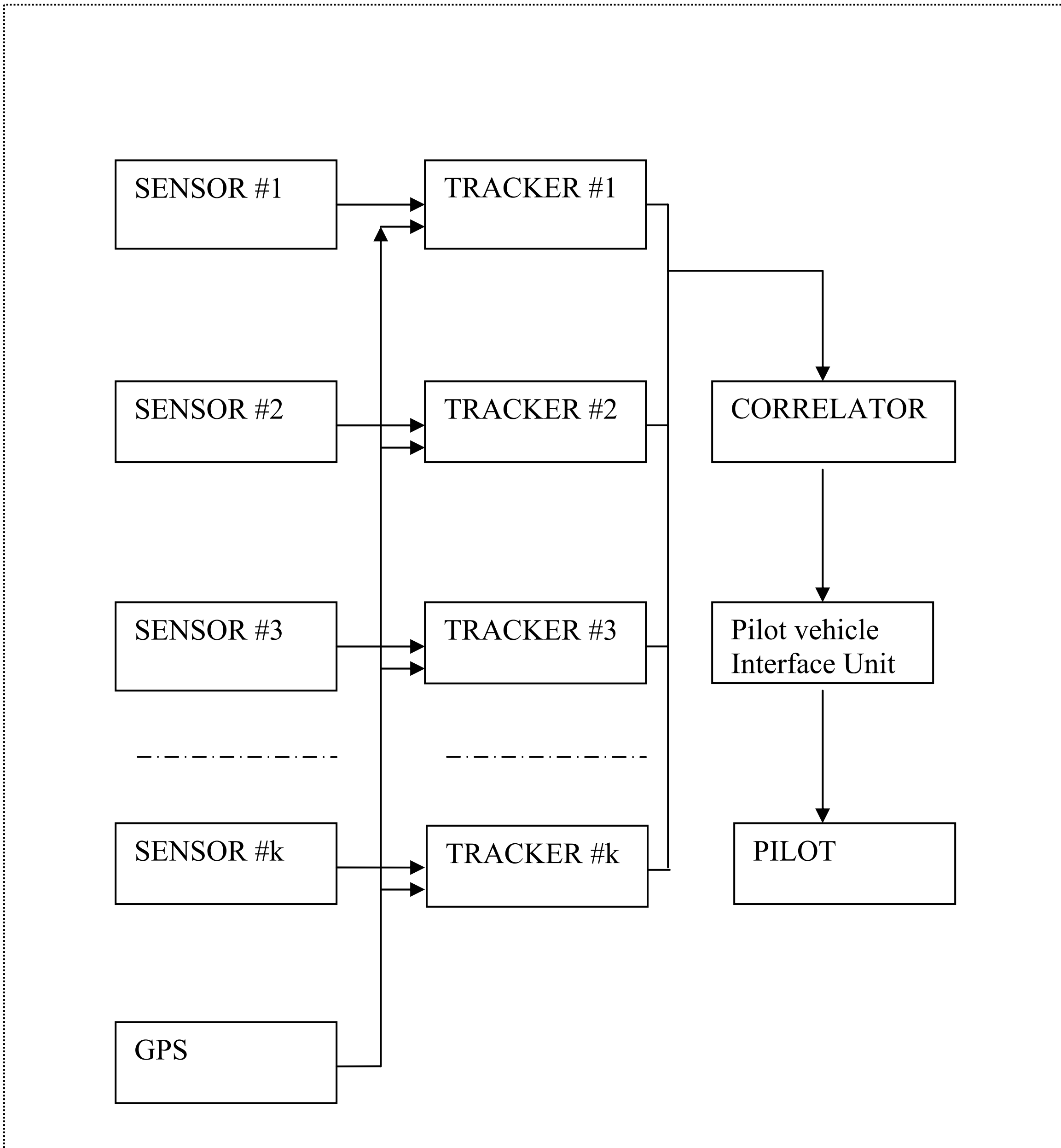
F. Updated state vector (U):

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

where: U = Noise Vector
Φ = Transition Matrix
Q = Noise Covariance Matrix
R = Measurement Noise Matrix
X_k = State Vector at time k
P_k = State Covariance Matrix at time k
H = Jacobian Matrix
G = Gating Matrix
K = Kalman Gain Matrix
Z = Measurement vector

The Extended Kalman Tracker is one of the widely used trackers. Track accuracy is very good, but equations C, D, and E indicate that in every calculation for each sensor measurement, there is matrix inversion, which will slow down the total tracking process and degrades the track accuracy.

ARCHITECHTURE OF MULTI-SENSOR TRACK FUSION MODEL



The Alpha, Beta, Gamma Tracker

Mathematical model for the α,β, γ tracker can be defined as follows:

A. Position Update Algorithm(U):

$$X_{k+1} = X_k + \alpha * X_k$$

B. Velocity Update Algorithm(U):

$$V_{k+1} = V_k + (\beta / q * T) * X_k$$

C. Acceleration Update Algorithm(U):

$$A_{k+1} = A_k + \{\gamma / (q * T)^2\} * X_k$$

where: α, β, γ are fixed coefficient filter parameters.
q = number of scant =1.0
T = Sample Interval = 1.0/F
X_{k+1} = target position at time (k+1)
V_{k+1} = target Velocity at time (k + 1)
A_{k+1} = target Acceleration at time (k+1)
K = 1, 2, 3,…..N
X_0, V_0, A_0 are initial values.
$\beta = 2 * (2 - \alpha) - 4 * \mathrm{sqrt}(1 - \alpha)$
$\gamma = \beta^2 / (2 * \alpha)$
If $\alpha = 0.6$, Then $\beta = 0.3$, and $\gamma = 0.08$.

α, β, and γ trackers are widely used trackers, and they are simple algorithmic tracking models. In Kalata's paper [ref], he shows some of the tracking parameters that are mathematically equivalent to the Kalman Tracker.

Multi-Sensor Correlation Processor (MSCRP)

One of the simple models for Data Fusion technology is the Coefficient of Correlation Model. The MSCRP can be used to measure the relationship between two target feature vectors. Mathematically, the Coefficient of Correlation Processor can be expressed as [Jeun 1997]:

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

where $X = \{ X1, X2, \ldots\ldots\ldots\ldots Xk \}$
$Y = \{ Y1, Y2, \ldots\ldots\ldots\ldots Yk \}$
$X \bullet X = \Sigma(Xi \,.\, Xi)$
$X \bullet Y = \Sigma(Xi \,.\, Yi)$
$Y \bullet Y = \Sigma(Yi \,.\, Yi)$
X and Y are target feature vectors

Properties of the Coefficients of Correlation Processor are:

(a) Show that Rxy =1.0 if X=Y

proof : Since $R_{XY} = X \bullet Y / (X \bullet X - X \bullet Y + Y \bullet Y)$

and $X = Y$

then

$X \bullet X = \Sigma(Xi . Xi)$

$X \bullet Y = \Sigma(Xi.Xi)$

$Y \bullet Y = \Sigma(Xi . Xi)$

by substitution, we have:

$Rxy = \Sigma(Xi . Xi)/\{\Sigma(Xi . Xi) + \Sigma(Xi . Xi) - \Sigma(Xi . Xi)\}$

$= \Sigma(Xi . Xi)/\Sigma(Xi . Xi)$

$= 1.0$

therefore $Rxy = 1.0$ for $X=Y$

(b) Show that $Rxy = 0.0$ for $X=0$ and $Y =/0$

proof: Since $Rxy= X\bullet Y/(X\bullet X + Y\bullet Y - X\bullet Y)$

and $X = \{ 0., 0., ...0. \}$

and $Y = \{ Y1, Y2, ...Yp \}$

by substitution, we have:

$X\bullet X = \Sigma(0. 0) = 0.0$

$X\bullet Y = \Sigma(0. yi) = 0.0$

$Y\bullet Y = \Sigma(Yi . Yi) = k=/0$, k is a non zero

that is $Rxy = 0/(0 - 0 + k) = 0 / k = 0$

(c) Show that $Rxy = 0$ for $X =/0$ and $Y = 0$

proof: since $Rxy = X\bullet Y/(X\bullet X + Y\bullet Y - X\bullet Y)$

and $X = \{ x1, x2, ...xk\}$

and $Y = \{ 0, 0, ...0 \}$

$X\bullet X = \Sigma(xi.xi) = k=/0$, k is a non zero

$X\bullet Y = \Sigma(xi.0) = 0$

$Y\bullet Y = \Sigma(0.0) = 0$

by substitution, we have:

$Rxy = 0/(k - 0 + 0) = 0/k= 0.0$

Decision rules concerning the Multi-Sensor Correlation Processor are:

(1) If the Coefficient of Correlation (R_{xy}) satisfies the following:

$0.95 <= R_{xy} <= 1.0$

then the feature vector X and the feature vector Y are most likely correlated.

(2) If the Coefficient of Correlation (R_{xy}) satisfies the following:

$0.0 <= R_{xy} < 0.95$

then the feature vector X and the feature vector Y are most likely not correlated.

The Simulated Information for the Alpha, Beta, Gamma Tracker

The tracker is one of the most important components of the new Multi-Sensor Track Fusion Model (MSTFM). Its performance will directly affect the MSTFM outcome; therefore it needs a separate evaluation. The following math models serve as simulated target projectiles:

target #1:

$$X1 = A\,t^2 + B\,t + C$$

where $A = 1.0$, $B = 3.0$, $C = 4.0$

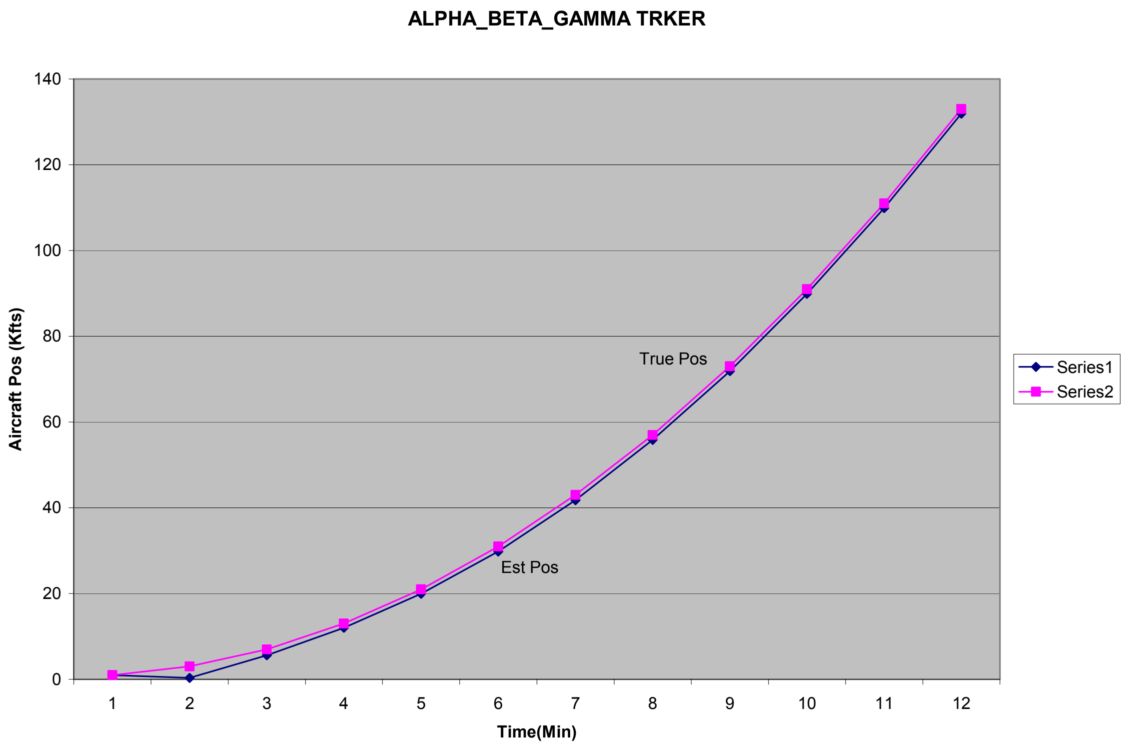
target #2:

$$X2 = A \exp(-B\,t) + C$$

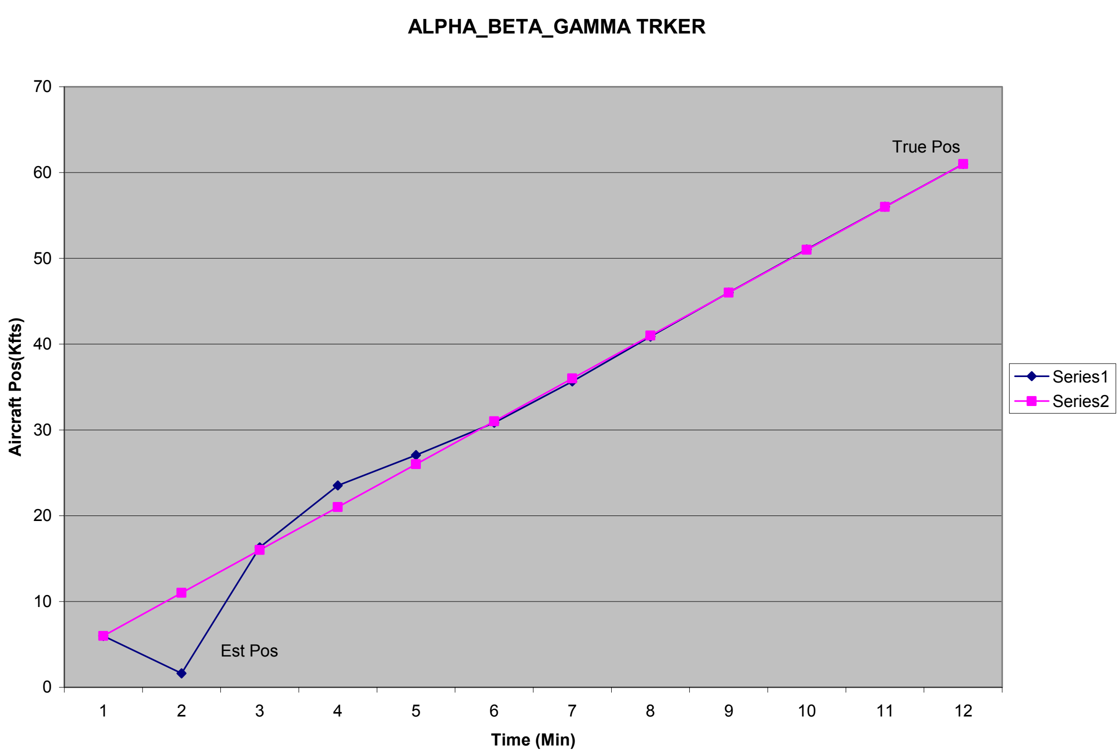
where $A = 0.2$, $B = 0.3$, $C = 4.0$

The following graphs (#1) and graph (#2) display the output of the tracker; the curves indicate estimated target projectile and the actual target projectile. The root mean square errors for both target #1 and target #2 are developed from the estimated target projectile and actual target projectile. For the simulation results, the root mean square errors for both target projectiles are less then 1.2 percent.

< Target #1>



< Target #2>



Simulation for Multi-Sensor Track Fusion

To evaluate the power of the new Multi-Sensor Track Fusion Model, we use the Simulation data from three mathematical target projectiles as following:

target #1: $X1(t) = 0.3\, t^2 – 1.5\, t + 6.3$

$P1(t) = 0.3\, t^2 – 1.5\, t + 6.3$ ---Position of target #1

$V1(t) = 0.6\, t – 1.5$ ---Velocity of target #1

$A1(t) = 0.6$ ---Acceleration of target #1

The feature vector for target #1 will be denoted as follows:

$T1= \{ P1, V1, A1\}$

target # 2: $X2(t) =7.0 \log (t) + 1$

$P2(t) =7.0 \log (t) + 1$ ---Position of target #2

$V2(t) = 7.0 / t$ ---Velocity of target #2

$A2(t) = - 7.0 / t^2$ ---Acceleration of target #2

The feature vector for the target #2 will be denoted as follows:

$T2 = \{ P2, V2, A2\}$

target #3: $X3(t) = A \exp (- 0.1\, t)$

$P3(t) = A \exp (-0.1\, t)$ ---Position of target 3

$V3(t) = -0.1\, A \exp (- 0.1\, t)$ ---Velocity of target #3

$A3(t) = 0.01\, A \exp (-0.1\, t)$ ---Acceleration of target #3

The feature Vector for target #3 will be denoted as follows:

$T3 = \{P3, V3, A3\}$

The decision of the Multi-Sensor Track Fusion Model is based on the coefficient of correlation between two feature vectors. For example, if target #1 and target #2 have a coefficient of correlation equal to one, then target #1 and target #2 are most likely identical to each other. However, if target #1 and target #2 have a coefficient of correlation that is close to zero, then target #1 and target #2 are most likely distinct targets.

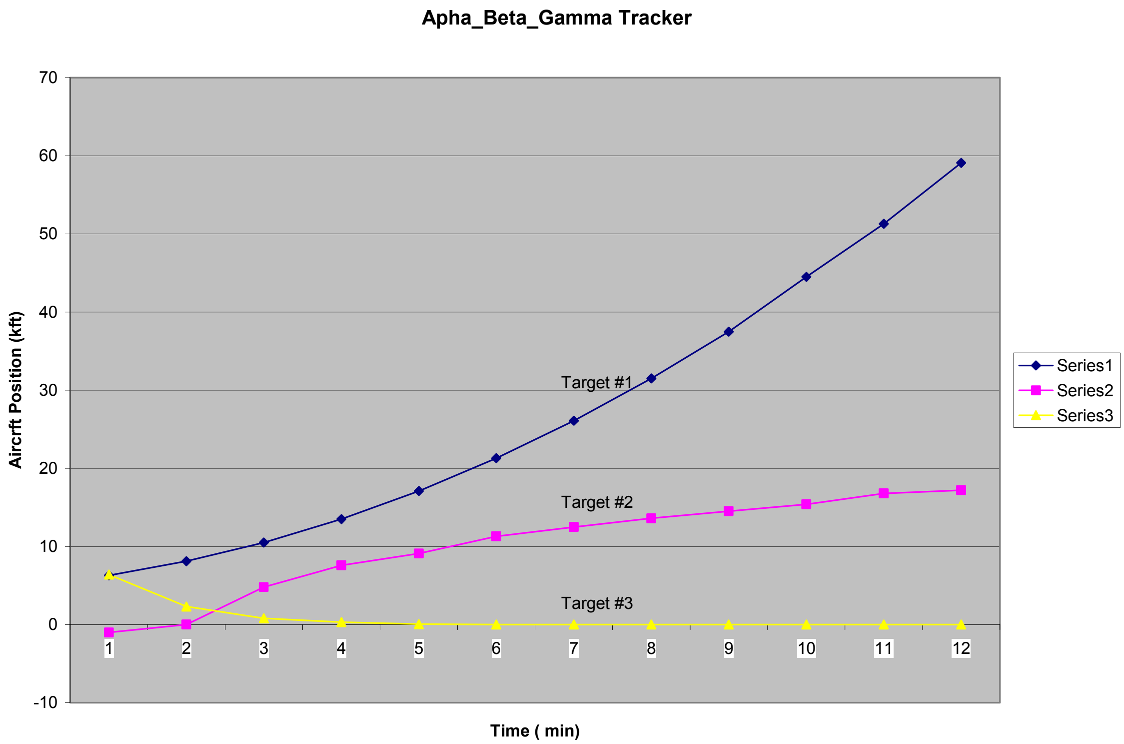
This simulation consists of two cases:

Case #1:

Considering the case of three sensors; Radar, Electronic Warfare (EW), and Communication, Navigation and Identification (CNI). Three distinct targets are being tracked by three alpha-beta-gamma trackers. Tracer #1 is tracking target #1; tracer #2 is tracking target #2; and tracer #3 is tracking target #3. The Multi-sensor Correlation Processor inside the Multi-Sensor Track Fusion Model estimates the coefficient of correlation among the feature vector of target #1, feature vector of target #2, and feature vector of target #3. All coefficients of correlation are not equal to one. Therefore all three targets are considered distinct.

Case #2:

Considering the similar case of three sensors, and one target is being tracked by three alpha-beta-gamma trackers. Again as in case #1, the Multi-Sensor Correlation Processor is used to calculate the coefficient of correlation between all targets. As the result of the calculation, all coefficients of correlation are equal to one, therefore the Multi-Sensor Track Fusion Model decides that there is only one target and it is the fused target.



Conclusions

In the future, every surveillance and fighter aircraft will be equipped with multiple sensors such as radar, electronic warfare, and communication, navigation and identification. These sensors need to be integrated in order to function together properly. The theoretical way to integrate the multi-sensor information is to use multi-sensor information fusion technology.

The new multi-sensor track fusion model is one of the theoretical methods to integrate the multi-sensor track information. No fusion implies no integration. The new Multi-Sensor Track Fusion Model is mathematically simple - no matrix inversion is needed and therefore processing speed is faster and less computer memory resources are required. The new Multi-Sensor Track Fusion Model does not use any matrix and vector processing in its model equations. Therefore it is easier to implement in any practical computer language for real time applications.

The track accuracy is over 98 percent as indicated by the simulation for the Alpha-Beta-Gamma tracker. The track fusion error is less then one percent, as indicated by the simulation for the Multi-Sensor Track Fusion Model.The new Multi-Sensor Track Fusion Model has been proven conceptually by mathematical simulation, but for future real time applications, this new model needs real time verification.

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