MULTI-PLATFORM MULTI-TARGET TRACKING FUSION VIA COVARIANCE INTERSECTION: USING FUZZY OPTIMISED MODIFIED KALMAN FILTERS WITH MEASUREMENT NOISE COVARIANCE ESTIMATION

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Abstract

Presented in this paper is a detailed novel approach to tracking multiple moving targets from multiple moving platforms and fusing the individual estimates within platform centric nodes via covariance intersection. The approach presents a method of deconstructing the target model into a nonlinear element and a Kalman Filter, modelling the target position and velocity vectors of the targets. The method avoids the increased complexity of using Extended Kalman Filters. The model state noise covariance is restructured by considering the source of the noise within the simplified imposed model and the measurement noise covariance is estimated from a single coefficient optimized moving average filter. The filter coefficient is optimally determined by the minimization of the variance of the Frobenius norm of the current estimated measurement covariance matrix, via a fuzzy logic feedback structure.

1 Introduction

Advances in technology, network enabled capability, and the needs of the ever more complex battlespace, have made it both necessary and possible to track targets using multiple sensors. The tracking objective is to collect sensory data from the surveillance volume containing one or more potential targets of interest and then partition the sensory data into sets of observations measured from the same target. The tracking algorithm is composed of three steps between time scans: prediction, data association and state update or filtering. Single sensor based systems can monitor objects with a precision and accuracy that depends on the sensor characteristics. Whereas, multi-sensor systems, observing the target, can obtain multiple viewpoints, extended coverage both spatially and temporally, reduce ambiguity and obtain a more precise estimate of object kinematics. In the battlespace multiple sensors can provide diverse information applicable to timely decision-making, allowing appropriate responses to perceived threats. To exploit the capability of such systems, techniques and technologies need to be developed. This paper presents a novel approach to tracking multiple moving targets from multiple platforms.

The technique presented in this is paper based on deconstructing the target model into nonlinear elements and using a Kalman Filters to estimate and model target kinematics – position and velocity vectors. The model state noise covariance is restructured by considering the source of the noise within the simplified imposed model. The measurement noise covariance is estimated from an optimised single coefficient moving average filter, in the sense of minimising the variance of the Frobenius norm of the current estimated measurement covariance matrix, via fuzzy logic based optimisation.

2 Kalman Filtering

The Kalman Filter is an efficient recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. The Kalman filter has become a de facto tracking solution. With all its drawbacks, it is still most widely used technique. In this paper we present a restructured form of this filter, but to understand our restructuring a basic overview of Kalman Filter is presented first.

The complete set of filter equations is shown in equations (1) to (7) representing the state estimate of the target.

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{A}_k \hat{\mathbf{x}}_{k|k} + \mathbf{B}_k \mathbf{u}_k \tag{1}$$

$$\hat{\mathbf{y}}_{k+1|k} = \mathbf{C}_{k+1} \hat{\mathbf{x}}_{k+1|k} \tag{2}$$

$$\hat{\mathbf{y}}_{k+1|k+1} = \hat{\mathbf{y}}_{k+1|k} + \mathbf{D}_{k+1} \mathbf{u}_{k+1} \tag{3}$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{k|k} \mathbf{A}_k^T + \mathbf{Q}_k \tag{4}$$

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^T \left(\mathbf{R}_{k+1} + \mathbf{C}_{k+1} \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^T \right)^{-1} \tag{5}$$

$$\mathbf{P}_{k+1|k+1} = \left(\mathbf{I} - \mathbf{K}_{k+1} \mathbf{C}_{k+1} \right) \mathbf{P}_{k+1|k} \tag{6}$$

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1} \left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1|k+1} \right) \tag{7}$$

This form includes external control inputs in the form of the $\mathbf{u}_k$ to the state which for a tracking solution can be considered as zero as they are unknown and more importantly will primarily only affect the acceleration terms of the state vector. These acceleration effects will affect the structure of the filter and will be considered in section 5. Here the state noise covariance matrix $\mathbf{Q}_k$ and the measurement noise covariance matrix $\mathbf{R}_{k+1}$ can be estimated offline structurally but the ratio of the magnitudes of their normed values is unclear. Both the structure and the normed ratio are key performance metrics for a Kalman Filter and most attempts to choosing them are flawed. The structure of the filter in equations (1) to (7) shows a recursive estimate of the state covariance matrices $\mathbf{P}_{k|k}$ & $\mathbf{P}_{k+1|k}$; if the $\mathbf{Q}_k$ and $\mathbf{R}_{k+1}$ matrices are constant then these covariances can be calculated off line, reducing the computation load. However, in an adaptive filtering scheme the recursion is still required.

3 Nonlinear Target Positional Estimator

Kalman filters are Bayes optimal; extended filters have been used to replace nonlinear process and measurement equations with an approximate linear system composed of the partial derivatives of the nonlinear functions. Extended Kalman Filters work well if the linearization errors are small and the system operates within a restricted range [1]. Their accuracy degrades otherwise [3]. It is well known that naïve linearization can introduce biases or errors in the covariance calculations that degrade filter performance [15]. A body of work exists that has looked into the stability and improvements of the EKFs and work presented in [2][11] and [2][4][5][6][9] proposes new ways of looking at EKF implementation to avoid problems faced in using nonlinear Extended Kalman Filtering with all of its inherent implementation problems.

Here we present a scheme that circumvents the issues plaguing EKF; the method is based on abstracting the nonlinear elements of the state estimator into a target positional estimate via a least squares method before the application of the restructured Kalman Filter discussed in section 4. The measurements are considered as lines of bearing and elevation from generic type sensors with their associated noise.

Consider an idealized i^{th} target positional estimator shown in figure 3.1. Here $\mathbf{p}_i$ is the sensing platform position, $\mathbf{p}_i(0)$ is normal of the target directional vector passing through the origin – this is the closest point to the origin of the extrapolated line through the target estimate and the sensing platform position, $\mathbf{u}_i$ is the unit vector along the target directional vector and $\hat{\mathbf{t}}_i$ is the i^{th} target positional estimate.

$\mathbf{u}_i$ can be given in terms of the bearing angle θ and the elevation angle ϕ as

$$\mathbf{u}_i = \begin{bmatrix} \cos\phi\sin\theta \\ \cos\phi\cos\theta \\ \sin\phi \end{bmatrix} \tag{8}$$

This vector has the following properties

$$|\mathbf{u}_i| = 1 \tag{9}$$

$$\mathbf{u}_i^T\mathbf{u}_i = 1 \tag{10}$$

Now consider an error vector $\mathbf{e}_i$ given as

$$\mathbf{e}_i = \hat{\mathbf{t}} - \hat{\mathbf{t}}_i \tag{11}$$

where $\hat{\mathbf{t}}$ is the best estimate of the target position. This requires an estimate of each $\hat{\mathbf{t}}_i$ from the measured bearing and elevation incorporated into the $\mathbf{u}_i$ for each sensing platform. Consider first how to express the sensing platform position $\mathbf{p}_i$ in terms of the normal vector $\mathbf{p}_i(0)$.

$$\mathbf{p}_i = \mathbf{p}_i(0) + \mathbf{u}_i\beta_i \tag{12}$$

By pre-multiplying this equation by $\mathbf{u}_i^T$ & observing that $\mathbf{u}_i^T\mathbf{p}_i(0) = 0$ & $\mathbf{u}_i^T\mathbf{u}_i = 1$ from equation (10) β_i can be found as

$$\beta_i = \mathbf{u}_i^T\mathbf{p}_i \tag{13}$$

Now the normal vector can be expressed as

$$\begin{aligned}\mathbf{p}_i(0) &= \mathbf{p}_i - \mathbf{u}_i\beta_i \\ &= \mathbf{p}_i - \mathbf{u}_i\mathbf{u}_i^T\mathbf{p}_i \\ &= \left(\mathbf{I} - \mathbf{u}_i\mathbf{u}_i^T\right)\mathbf{p}_i\end{aligned} \tag{14}$$

In a similar manner each estimate of the target position can be expressed as

$$\hat{\mathbf{t}}_i = \mathbf{p}_i(0) + \mathbf{u}_i\alpha_i \tag{15}$$

Now consider a least squares cost function of the target positional errors

$$\varepsilon = \sum_{i=1}^{n}\mathbf{e}_i^T\mathbf{e}_i \tag{16}$$

And minimise this with respect to each α_i

$$\frac{\partial\varepsilon}{\partial\alpha_i} = 2\mathbf{e}_i^T\frac{\partial\mathbf{e}_i}{\partial\alpha_i} = 0 \tag{17}$$

$$\frac{\partial\mathbf{e}_i}{\partial\alpha_i} = -\frac{\partial\mathbf{t}_i}{\partial\alpha_i} = -\mathbf{u}_i \tag{18}$$

This implies that

$$\mathbf{e}_i^T\mathbf{u}_i = 0 \tag{19}$$

$$\left(\hat{\mathbf{t}} - \hat{\mathbf{t}}_i\right)\mathbf{u}_i = 0 \tag{20}$$

$$\hat{\mathbf{t}}^T\mathbf{u}_i - \mathbf{p}_i^T(0)\mathbf{u}_i - \alpha_i\mathbf{u}_i^T\mathbf{u}_i = 0 \tag{21}$$

Finally α_i and the error can be expressed as

$$\alpha_i = \hat{\mathbf{t}}^T\mathbf{u}_i \tag{22}$$

and

$$\mathbf{e}_i = \left(\mathbf{I} - \mathbf{u}_i\mathbf{u}_i^T\right)\hat{\mathbf{t}} - \mathbf{p}_i^T(0) \tag{23}$$

Now minimise the same cost function of equation (16) with respect to $\hat{\mathbf{t}}$ from the following

$$\frac{\partial \varepsilon}{\partial \hat{\mathbf{t}}} = \sum_{i=1}^{n} 2\mathbf{e}_i^T \frac{\partial \mathbf{e}_i}{\partial \hat{\mathbf{t}}} = \mathbf{0}^T \tag{24}$$

$$\frac{\partial \mathbf{e}_i}{\partial \hat{\mathbf{t}}} = \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right) \tag{25}$$

which implies from equations (20) to (25)

$$\sum_{i=1}^{n} \mathbf{e}_i^T \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right) = \mathbf{0}^T \tag{26}$$

$$\sum_{i=1}^{n} \left[\left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right)\hat{\mathbf{t}} - \mathbf{p}_i(0)\right]^T \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right) = \mathbf{0}^T \tag{27}$$

which by rearranging gives

$$\hat{\mathbf{t}} = \left[\sum_{i=1}^{n} \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right)\right]^{-1} \left[\sum_{i=1}^{n} \mathbf{p}_i(0)\right] \tag{28}$$

which can be written as

$$\hat{\mathbf{t}} = \left[\sum_{i=1}^{n} \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right)\right]^{-1} \left[\sum_{i=1}^{n} \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right)\mathbf{p}_i\right] \tag{29}$$

noting that

$$\left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right)^T \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right) = \left(\mathbf{I} - \mathbf{u}_i \mathbf{u}_i^T\right) \tag{30}$$

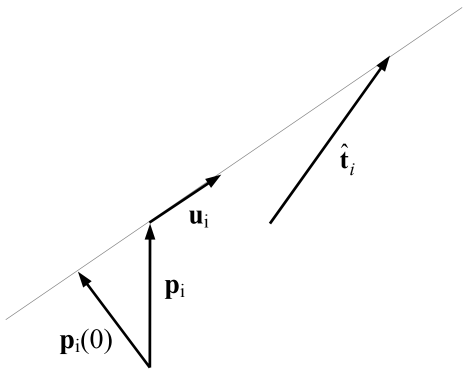

Figure 3.1: Target Position Estimation

4 Optimal Restructured Kalman Filter with Measurement Noise Covariance Estimation

We have established the fact that multi-sensor multi-target tracking is useful; Kalman Filtering on its own is not sufficient to solve this problem, introduction of Covariance Intersection will allow extending the Kalman Filter. To achieve all this we would need to restructure the Kalman Filter implementation. The full derivation of restructuring and inclusion of covariance intersection in the Kalman Filter is presented here.

If the idealised metrics of a target can be considered as its position vector and its velocity vector; and that the velocity vector only changes due to small control inputs or terrain change, in the case of a ground target or air buffeting in the case of an aircraft, then if these accelerations are considered as Gaussian White noise to the required metrics we can restructure the filter as follows.

The state equations of the imposed model can now be represented as

$$\begin{bmatrix}\mathbf{x}_{k+1}\\ \mathbf{a}_{k+1}\end{bmatrix} = \begin{bmatrix}\mathbf{A}_k & \mathbf{F}_k\\ \mathbf{I}_l & \mathbf{O}_{l,l}\end{bmatrix}\begin{bmatrix}\mathbf{x}_k\\ \mathbf{a}_k\end{bmatrix} + \begin{bmatrix}\mathbf{O}_{n,l}\\ \mathbf{I}_l\end{bmatrix}\boldsymbol{\omega}_k \tag{31}$$

$$\mathbf{y}_k = \begin{bmatrix}\mathbf{C}_k & \mathbf{O}_{m,l}\end{bmatrix}\begin{bmatrix}\mathbf{x}_k\\ \mathbf{a}_k\end{bmatrix} + \mathbf{v}_k \tag{32}$$

where $\boldsymbol{\omega}_k$ is a Gaussian White noise vector which has a zero mean vector that is

$$E\{\boldsymbol{\omega}_k\} = \mathbf{0} \tag{33}$$

and a noise covariance given by

$$E\{\boldsymbol{\omega}_k \boldsymbol{\omega}_k^T\} = \mathbf{Q}_k \tag{34}$$

the covariance matrix will generally be diagonal and probably and represent the covariance of a Gaussian White noise unit variance vector. This is valid since the noise on the state is unknown and the normed ratio between the state covariance and the measurements noise will be compensated for in the estimate of the measurement noise covariance matrix. It is trivial to show that the performance of the estimator is dependent on the structure and the normed ratio of the two covariance matrices. Unit variance Gaussian White noise is therefore the best estimate for the state noise.

Now consider the structure of the augmented state matrix.

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{F}_k \mathbf{a}_k \tag{35}$$

$$\mathbf{a}_{k+1} = \boldsymbol{\omega}_k \tag{36}$$

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{F}_k \boldsymbol{\omega}_{k-1} \tag{37}$$

here the $\mathbf{A}_k$ and $\mathbf{F}_k$ matrices are structures are derived as velocity as the first differential of the position vector and the acceleration as the second differential as follows

$$\mathbf{A}_k = \begin{bmatrix}\mathbf{I}_3 & \tau\mathbf{I}_3\\ \mathbf{0}_{3,3} & \mathbf{I}_3\end{bmatrix} \tag{38}$$

$$\mathbf{F}_k = \begin{bmatrix}\frac{1}{2}\tau^2\mathbf{I}_3\\ \tau\mathbf{I}_3\end{bmatrix} \tag{39}$$

here τ is the sampling time. From equation (36) the acceleration vector is considered to be a direct transmission of the state noise and becomes incorporated into the state estimate via the $\mathbf{F}_k$ matrix. The modified covariance then becomes

$$E\{\mathbf{F}_k \boldsymbol{\omega}_{k-1} \boldsymbol{\omega}_{k-1}^T \mathbf{F}_k^T\} = \mathbf{F}_k \mathbf{Q}_{k-1} \mathbf{F}_k^T \tag{40}$$

where

$$E\{\mathbf{F}_k \boldsymbol{\omega}_{k-1}\} = \mathbf{0} \quad (41)$$

The complete set of filter equations then becomes

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{A}_k \hat{\mathbf{x}}_{k|k} \quad (42)$$

$$\hat{\mathbf{y}}_{k+1|k} = \mathbf{C}_{k+1} \hat{\mathbf{x}}_{k+1|k} \quad (43)$$

$$\hat{\mathbf{y}}_{k+1|k+1} = \hat{\mathbf{y}}_{k+1|k} \quad (44)$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}_k \mathbf{P}_{k|k} \mathbf{A}_k^T + \mathbf{F}_k \mathbf{Q}_{k-1} \mathbf{F}_k^T \quad (45)$$

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^T \left(\mathbf{R}_{k+1} + \mathbf{C}_{k+1} \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^T \right)^{-1} \quad (46)$$

$$\mathbf{P}_{k+1|k+1} = (\mathbf{I} - \mathbf{K}_{k+1} \mathbf{C}_{k+1}) \mathbf{P}_{k+1|k} \quad (47)$$

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1} \left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1|k+1} \right) \quad (48)$$

These assumptions are only valid when the target is travelling in a straight line and at a constant velocity. If however the target changes direction then the effective noise seen by the estimator will increase. This noise cannot be considered as Gaussian White noise during target manoeuvres but it can be reasonably assumed to be aggregated as measurement noise. This aggregated measurement noise requires some form of estimator which estimates both the structure of the measurement noise covariance matrix and its normed ratio with respect to the state covariance matrix. Presented is a method of achieving this.

Consider the error between the actual measurement vector and the estimated one

$$\mathbf{e}_{k+1} = \mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1|k+1} \quad (49)$$

by substituting noisy and estimated values from the complete filter equations this becomes

$$\mathbf{e}_{k+1} = \mathbf{C}_{k+1} \mathbf{x}_{k+1} + \mathbf{v}_{k+1} - \mathbf{C}_{k+1} \hat{\mathbf{x}}_{k+1|k} \quad (50)$$

and rearranging to give the noise vector as

$$\mathbf{v}_{k+1} = \mathbf{e}_{k+1} - \mathbf{C}_{k+1} \left(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k} \right) \quad (51)$$

now the covariance of this noise vector is the measurement noise covariance matrix $\mathbf{R}_{k+1}$ which can be found as follows

$$\mathrm{cov}(\mathbf{v}_{k+1}) = \mathrm{cov}\left(\mathbf{e}_{k+1} - \mathbf{C}_{k+1} \left(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k} \right) \right) \quad (52)$$

$$\mathbf{R}_{k+1} = \mathrm{cov}(\mathbf{e}_{k+1}) + \mathbf{C}_{k+1} \mathrm{cov}\left(\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k} \right) \mathbf{C}_{k+1}^T \quad (53)$$

$$\mathbf{R}_{k+1} = \mathbf{E}_{k+1} + \mathbf{C}_{k+1} \mathbf{P}_{k+1|k} \mathbf{C}_{k+1}^T \quad (54)$$

now finally the estimate of measurement error covariance can be found by using a moving average filter

$$\hat{\mathbf{E}}_{k+1} = (1-\alpha) \mathbf{e}_{k+1} \mathbf{e}_{k+1}^T + \alpha \hat{\mathbf{E}}_k \quad \alpha \in [0,1] \quad (55)$$

This filter has a steady state gain of unity and α corresponds to a recursive moving average filter of n samples so

$$\alpha = \frac{(n-1)}{n} \quad (56)$$

This can be rearranged to find n from a desired α as

$$n = \frac{1}{(1-\alpha)} \quad (57)$$

This value of α is optimally estimated using a fuzzy logic feedback method described in the next section.

5 Fuzzy Logic Based Optimization

The noise in the system is non-Gaussian when the platform is going through a turn manoeuvre. This has consequences for the validity of the noise models within the filter. A method of ameliorating these consequences is to introduce feedback into the system which minimises some metric of the system until such a time as the assumptions about the noise model become more realistic. The parameters optimised using classical methods, involving deterministic variables, exhibit various shortcomings. The effects of the uncertainty attached to input information is often ignored altogether or only taken into account to a limited degree. Moving away from classical optimisation methods, fuzzy optimisation methods optimises objective functions and constraints, simultaneously. In this paper a fuzzy optimisation process has been adapted that characterises both objective function and constraints by membership functions and links them by linguistic conjunction: “and” (for maximisation) and “or” (for minimisation). The fuzzy optimisation by pseudo-goal, as proposed by Bellman and Zadeh in their seminal paper on decision making in fuzzy environment [11], is used to optimise the variance of the Frobenius norm of the measurement covariance; this technique ensures that the fuzzy objective function and fuzzy constraints both receive the same treatment.

Constraints:

1. The noise is non-Gaussian when the platform is in a turn manoeuvre, therefore the variance of the Frobenius Norm of the measurement covariance needs to be minimise
2. Restructuring premise is based on noise only being present in the system via small acceleration terms.

The candidate parameter that the feedback scheme will optimise is filter coefficient α of the measurement noise covariance matrix estimator in equation (55). In order for the optimisation to be meaningful a set of candidate, values from which the membership functions of the fuzzy logic will choose α, need to be chosen. Here a set of five membership functions has been chosen with a set of values for $\alpha \in \{0.8, 0.875, 0.9, 0.98, 0.999\}$, which corresponds to sampling counts of $n \in \{5, 8, 10, 50, 1000\}$. The membership functions are shown in figure 5.1 and are evenly distributed between a variance of zero and a maximum value which is determined by constant measurement.

A value for the variance at time $k\tau$ can be found using a recursive method with a fixed averaging constant. For this an estimate of the mean of the Frobenius norm of the measurement noise covariance matrix is required, this is given by

$$\eta_k = \left[Tr\left(\mathbf{R}_{k+1}^T \mathbf{R}_{k+1}\right) \right]^{\frac{1}{2}} \quad (58)$$

$$\mu_k = \lambda \mu_{k-1} + (1-\lambda)\eta_k \quad (59)$$

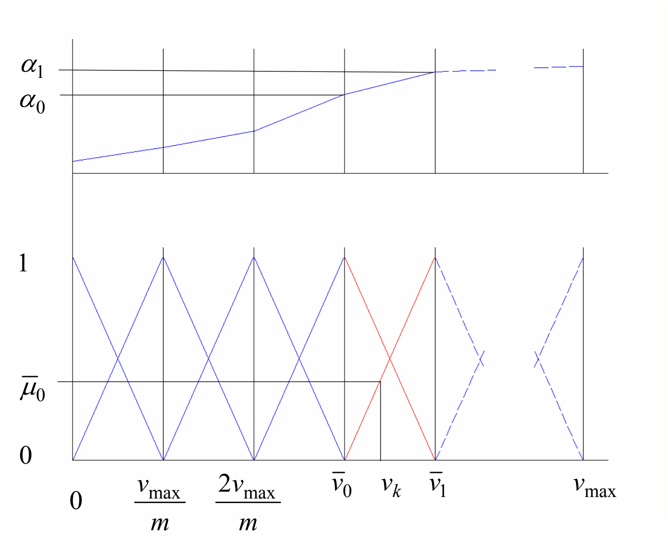

Figure 5.1: Fuzzy Inference Membership Functions

and the exact recursive variance is given by

$$v_k = \lambda v_{k-1} + (1-\lambda)\eta_k^2 + \lambda \mu_{k-1}^2 - \mu_k^2 \quad (60)$$

but can be approximated as

$$v_k = \lambda v_{k-1} + (1-\lambda)(\eta_k - \mu_k)^2 \quad (61)$$

here λ is the filter constant.

At each iteration, the value of v_k is checked against the last maximum $v_{\max}$ and substituted for it if it is larger. Then the membership function abscissa scale is determined as

$$\mathbf{v}^T = \begin{bmatrix} 0 & \frac{v_{\max}}{m} & \frac{2v_{\max}}{m} & \cdots & v_{\max} \end{bmatrix} \quad (62)$$

This set allows the fuzzification of the variance into grades of membership. To compute the membership function values of figure 5.1 the immediate neighbouring values, that the present variance exist between, are found as $\bar{v}_0$ and $\bar{v}_1$, the associated α set values α_0 and α_1; and hence the values of $\bar{\mu}_0$ and $\bar{\mu}_1$ the are found as

$$\bar{\mu}_0 = \frac{\bar{v}_1 - v_k}{\bar{v}_1 - \bar{v}_0} \quad (63)$$

and

$$\bar{\mu}_1 = 1 - \bar{\mu}_0 \quad (64)$$

these functions are effectively the fuzzy inference machine which combines the fuzzification with rule based fuzzy reasoning. Finally the optimized filter coefficient is given as a result of the defuzzification through the α set to give

$$\alpha = \bar{\mu}_0 \alpha_0 + \bar{\mu}_1 \alpha_1 \quad (65)$$

This simple linear combination produces an acceptable performance but further tuning of the α set and the membership function abscissa requires further research.

6 Covariance Intersection

In the case of decentralised sensor networks, as in this paper, to avoid consequences of redundant data on Kalman-type estimators, covariance information should be maintained. Maintaining consistent cross covariances in arbitrary decentralised networks is impossible [16]. Some fixed topologies of the decentralised networks can overcome some of the issues, but fails to deliver the benefit of reliability due to dependency issues raised in selecting specific topologies. Issues of conditional independence of the measurement errors from a sample to sample perspective in a Kalman Filter framework can also compromise its ability to guarantee reliable results [14].

Covariance Intersection can remove the issue of independence. In this paper we are considering two platforms, therefore two sets of tracking information need to be fused together to yield a coherent situational awareness, a set candidacy for Covariance Intersection. In generic form Covariance Intersection takes convex combination of mean and covariance estimates that are represented in the information space [15]. This convex combination is consistent in the sense that the resulting covariance hyper-ellipsoids are contained within the outer bounds of all of the covariance hyper-ellipsoids of each individual estimator. Equations (2) and (3) show a consistent covariance and mean estimate for a two part intersection scheme with a varying weight $\mu \in [0,1]$ [15].

$$\mathbf{P}_m = \left(\mu \mathbf{P}_a^{-1} + (1-\mu)\mathbf{P}_b^{-1}\right)^{-1} \quad (66)$$

$$\mathbf{x}_m = \mathbf{P}_m\left(\mu \mathbf{P}_a^{-1}\mathbf{x}_a + (1-\mu)\mathbf{P}_b^{-1}\mathbf{x}_b\right) \quad (67)$$

For an n part intersection a general uniform weighting scheme can be applied which can be varied as more information becomes available and as the reliability of the received data is determined. Equations (68) to (70) summarise this approach:

$$\mu = \frac{1}{n} \quad (68)$$

$$\mathbf{P}_m = \left(\frac{1}{n}\sum_{i=1}^{n} \mathbf{P}_i^{-1}\right)^{-1} \quad (69)$$

$$\mathbf{x}_m = \frac{1}{n}\mathbf{P}_m \sum_{i=1}^{n} \mathbf{P}_i^{-1}\mathbf{x}_i \quad (70)$$

7 Simulation

Presented is a simulation case study with one target and two sensing platforms. In this case they are considered to be an aircraft platform and a UAV at altitudes of 1000 metres and velocities of $150 ms^{-1}$ and $100\ ms^{-1}$ respectively. They track a fast moving ground hugging target moving at $50\ ms^{-1}$. Both air vehicles move around typical race tracks and the ground vehicle moves along a similar path for the purposes of simulation. Figure 7.1 shows their relative positions. The system is simulated in Matlab and Simulink. Gaussian White noise is introduced into the positional and angular measurements with zero mean and variances of 1.0 and 0.1 respectively. The introduction of noise at these levels induces considerable errors in the non linear target estimator which become apparent when a naïve Kalman Filtering approach is adopted.

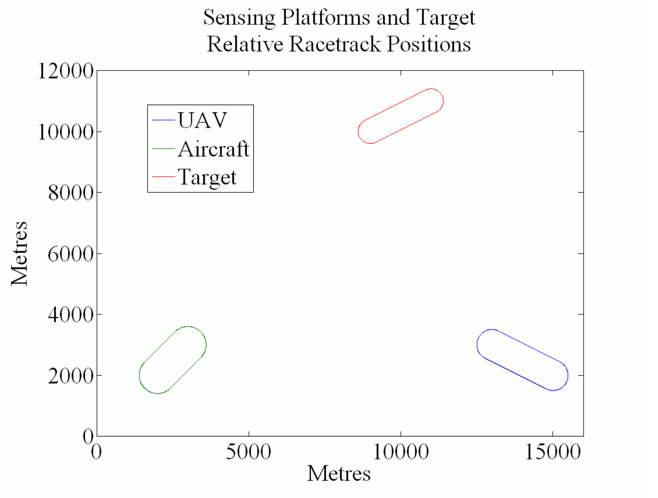

Figure 7.1: Relative Platform Positions

The results of the positional and velocity estimates can be seen in figure 7.7 whereas the noise free target position and velocity vectors are shown in figure 7.6. The simulation of the novel scheme position and velocity vectors given exactly the same environmental conditions is shown in figure 7.8 where the improvement in the position vector is marked and the velocity errors are reduced by an order of magnitude, thus making it a usable metric for positional prediction. This is also true even on the turning parts of the sensing platforms racetracks and that of the target. Here the state noise cannot be considered to be Gaussian and White since there are control inputs into the platforms which move them away from their zero mean operating points. However the system performs remarkable well even in these regions. This is because the optimising fuzzy logic feedback controlling the moving average filter constant recursively measures the variance and allows the system to adapt continually to any changes in the nature of the noise, re-calculating the state covariance matrices and estimating the measurement noise covariance matrix. The changes in the filter constant over the simulation run can be seen in figure 7.2 and the recursively measured variance and mean using a predetermined fixed filter constant, can be seen in figure 7.3 and 7.4 respectively. There is a clear correlation between these, driven by the fuzzy logical feedback of section 5, as the platforms manoeuvre accordingly around the racetracks. Finally the operation of the fuzzy logic is illustrated in figures 7.5 where the region of operation of the constantly varying fuzzy inference membership function value $\overline{\mu}_0$ is shown.

8 Conclusions

In this paper two key challenges have been addressed: the bearings-only tracking problem including cases involving observability problems, and the fusing of disparate sensor data to derive coherent situational awareness. The simulation results demonstrate the effectiveness of the proposed novel approach. The improvement in the platform position vectors and the velocity vector errors are reduced by an order of magnitude over the naïve Kalman filter approach. This makes the approach usable for target position and velocity prediction. The approach presented a method of deconstructing the target model into a nonlinear element and a Kalman Filter, modelling the target position and velocity vectors. The model state noise covariance is restructured by considering the source of the noise within the simplified imposed model and the measurement noise covariance is estimated from a single coefficient optimized moving average filter. The filter coefficient is optimally determined by the minimization of the variance of the Frobenius norm of the current estimated measurement covariance matrix, via a fuzzy logic feedback structure. Further work is required to improve the fuzzy logic based optimiser to allow tuning for any situation.

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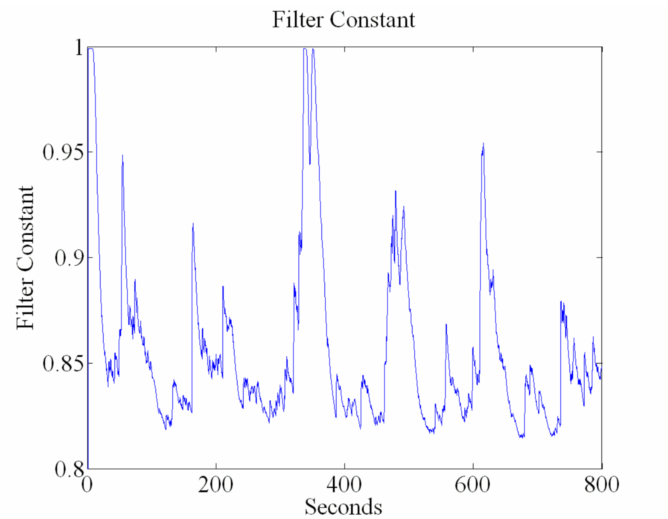

Figure 7.2: Filter Constant

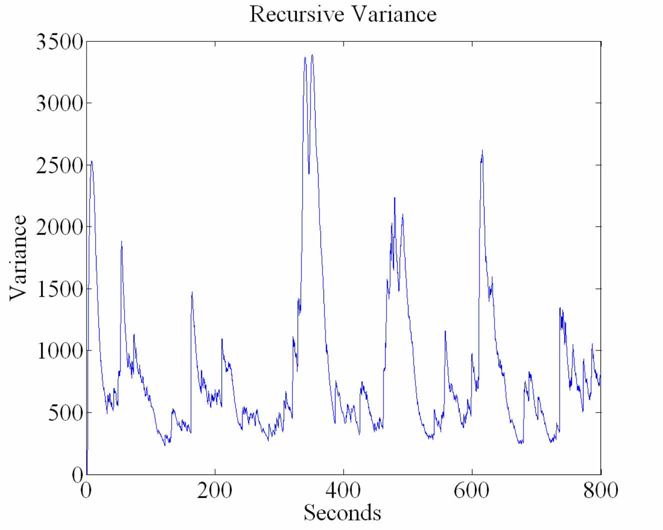

Figure 7.3: Recursive Variance

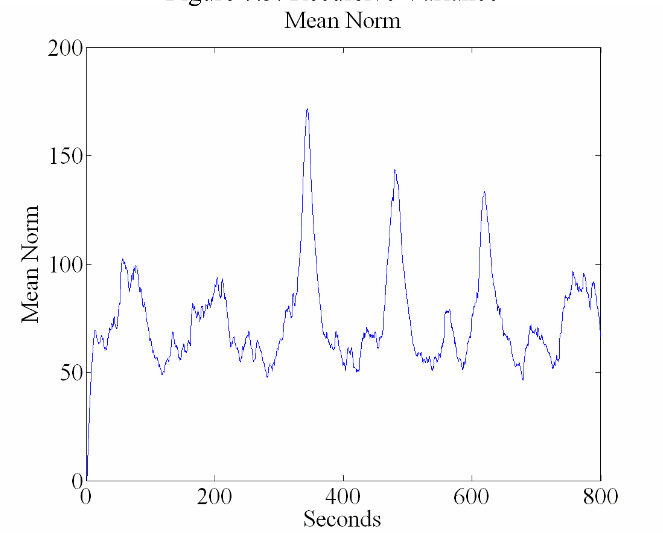

Figure 7.4: Mean of Norm

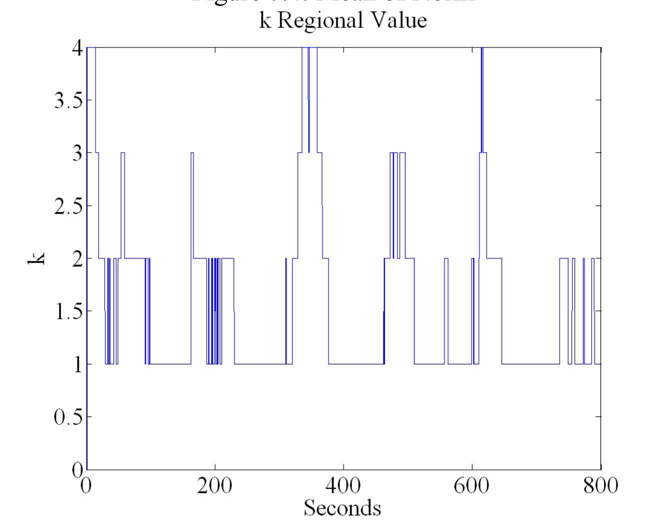

Figure 7.5: Region of Operation Value

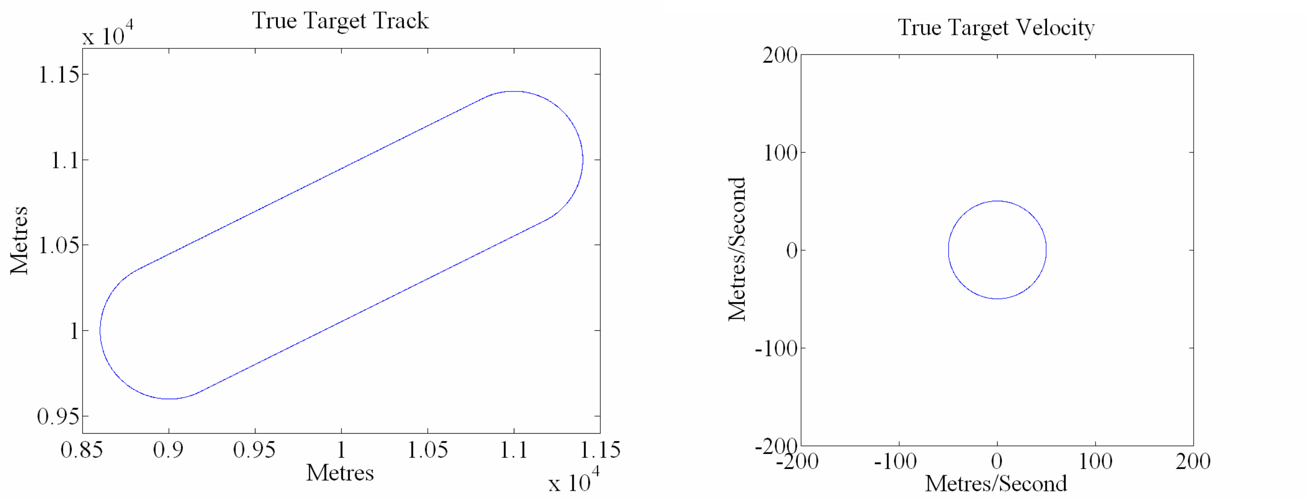

Figure 7.6: Actual target position

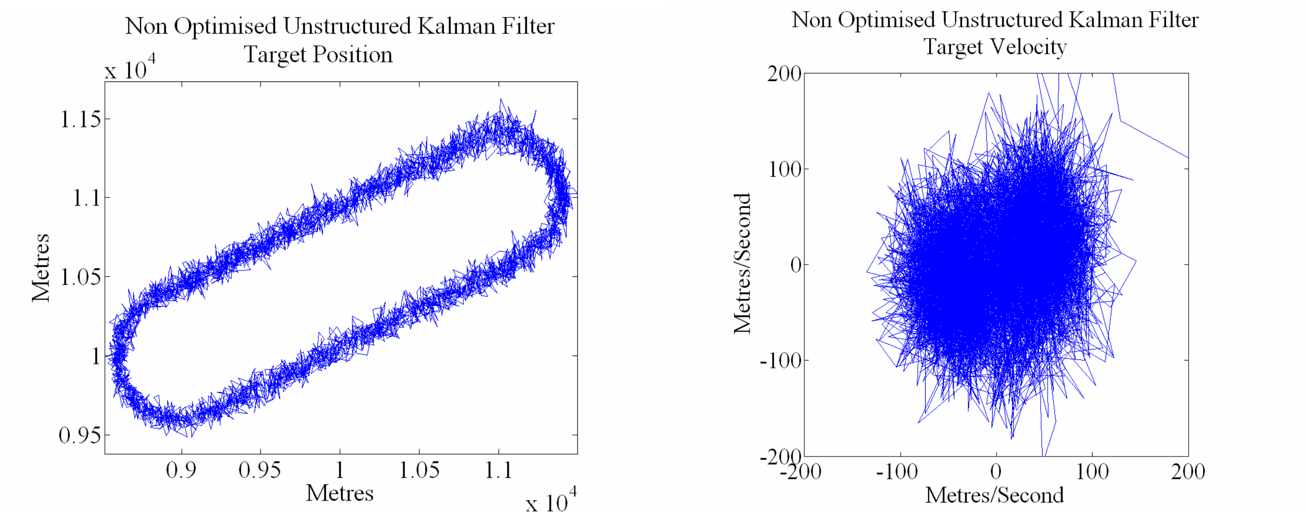

Figure 7.7: Position and velocity estimate from a naïve Kalman Filter

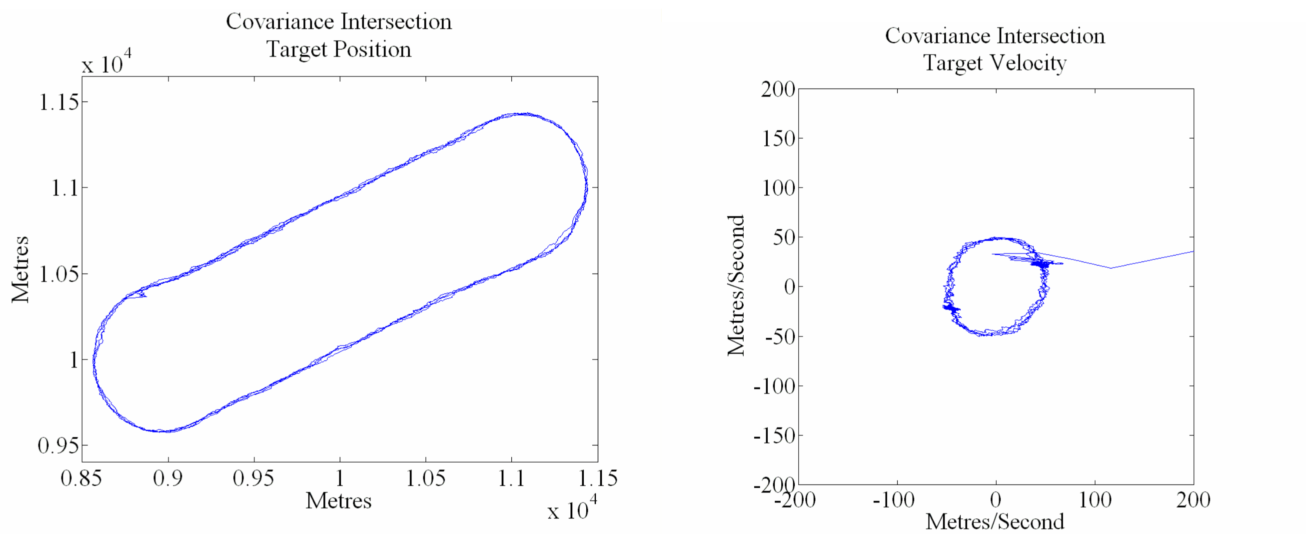

Figure 7.8: Position and velocity estimates from a proposed scheme