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Analysis of Variable Dimension Extended Kalman Filter for Maneuvering Target Tracking Systems

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ABSTRACT: *Variable dimension filter (VDF) with maneuver detector to the tracking systems is discussed. The objective of this detector is to provide both constant velocity and straight line flight path (known as maneuver mode). A detection scheme has been developed to determine that a maneuver is indeed occurring. Once a maneuver is detected, a different state model is used by the filter {i.e., new state components are added). The extent of the maneuver, as detected, is then used to yield an estimate for the extra state components, and corrections are made on the other state components {position and velocity). The tracking is then done with the augmented state model until it reverts to the normal model by another decision. A new tracking scheme (variable dimension Extended Kalman Filter VDEKF) that incorporates a simple Kalman filter and a detector has been analyzed. A powerful computer program in Matlab has been developed in order to conduct the simulation.*

Keywords: *Target tracking, Kalman filter, etc.*

I. INTRODUCTION

A number of different approaches to the maneuvering target problem have appeared in the literature recently.The most commonly used model, due to simplicity requirements, has been to model the target dynamics in rectangular coordinates system which results in a linear set of state equations. With this model an Extended Kalman Filtering algorithm is frequently used, both to provide current state variable estimates and, by a one-step prediction process, to linearize the next measurements vector. This method storks moderately well until the target makes an abrupt change in its trajectory in response to pilot or missile-guidance program commands, and often diverges from the true unknown values. The inherent problems of this approach can lead to large bias errors and sometimes complete filter divergence. In another method, given by Singer [1], the target acceleration was modeled as a random process with known exponential auto-correlation. The result of this approach when tracking a target moving at a constant velocity is that the filter is capable of tracking targets maneuvering, as above, but the quality of the estimate is degraded compared with the Kalman filter based on a rectilinear motion model. The tracking performance provided by the filter presented in this approach would often be below that obtained by a simpler filter, such as a least squares filter when tracking maneuverable targets moving at constant.The switching of models resembles somewhat the approach(using statistical theory) todrive an optimum maneuver detector for use with Singer's generalized tracking model [2]

II. PROBLEM OCCURRED IN TARGET TRACKING

The tracking problem is a state estimation problem, involving a radar tracking system that measures the position of an aircraft in two angular dimensions and one linear dimension for example, azimuth and elevation angles, plus slant range.If measurements are made at different points in time, and is recognizedthat the system itself is dynamic in the sense that the states change with time in a knownway, then both position and velocity coordinates can be estimated from the time sequenceof available measurements. Such a situation represents a filtering problem, and the solution results in a set of time functions representing the estimates of the system states[4].Filtering may be performed in either line-of-sight or Cartesian coordinates. It has been shown in [3] that, smoothing the data in line-of-sight coordinates has been shown to be undesirable because the linear model leads to large dynamic errors.

III. EXTENDED KALMAN FILTER STATE EQUATION

In the xyz filter, the measurements were transformed from polar to xyz coordinates before computation of the residuals (innovations) for insertion into the filter.A possible source of difficulty in the xyz filter arises because of the non-linearity of themeasurements. When the measurements are transformed from polar to xyz coordinates, themeasurements error covariance matrix R must be correspondingly transformed. The matrixused for transformation is normally based on the position estimates available before eachmeasurement. Before the first measurement, however, these estimates are greatly in error, and such a transformation results in a disorientation of the error ellipsoid corresponding toR. Since this ellipsoid is very flat due to the high accuracy of the range measurement, thisdisorientationcauses the filter to believe that the firm measurement is highly accurate in adirection in which is not. The result is a severe bias in the estimates, which persists of asurprisingly long period of time (almost throughout the trajectory).The remedy for this difficulty is quite simple and costs nothing in computation time. Sincethe target position indicated by the first measurement is much accurate thenthe prior estimate. We simply wait until the first measurement because available, and use the indicated position in deriving the transformation matrix for R. This trivial modification results is vastly improved performance.

While, the initial conditions (x(0/0), P(0/0)) are part of the problem statement and reflect the prior knowledge of x(t) before the filtering begins. The radar detects the position of the target is spherical coordinates r, θT and θE. The initial position in rectangular coordinates can be established through coordinate transformation by neglecting the measurement noises v(0). The initial velocities can be established by taking the difference of positions at two consecutive sampling points and dividing it by T. At least two stages are required to set up the initial velocities. Averaging may be extended over more stages. Of course, it delays the start of the filtering operation. If the target is maneuvering, multiple-stage pre-filtering may result in a poor velocity estimate.In general, most tracking filters are initialized after two position samples are received and/or a velocity estimate can be formed. A reasonable approach for filter initialization is to utilize the standard two - point initialization of the state estimate and covariance, and to begin the history growth at the third scan, which is generally the first time a small correlation gate region can be used reliably.

We see that filter gain is proportional to the inverse of S. Predicted residuals provide us with a useful tool for judging the performance of the filter in actual practice. By checking whether residuals indeed possess their (theoretical) statistical properties, we are able to assess the performance of the filter.The filter computations, as outlined in the foregoing analysis, involve the partial derivativematrix H(k+1) evaluated at predicted values of the variables x^(k+1/k) . The time-varyingJacobian - matrix cannot be precomputed because functions for it must be calculated in realtime.For the tracking filter under consideration, the real - time computation of EKF gain matrixis quite involved. This further complicated by numerical truncation errors due to wordlength initiation. when the filter needs to be implemented on microprocessor.Accurate tracking of maneuvering aircraft targets often requires the utilization of digitalfilters.

IV. VARIABLE DIMENSION FILTER (VDF)

Our approach to the VDF has been to develop a maneuver detector added to the trackingalgorithm that is designed for the constant - velocity, straight-line flight path (non-maneuver mode). A maneuver detector determines when the true tracker dynamics differfrom the postulated flight plan. When this occurs, a maneuver is detected, and the tracker is switched from non-maneuver to maneuver mode. Then the new tracker depend upon the maneuvering model is reinitialized using the most recent measurement data. Since it will take some time for this tracker to reacquire the track, considerable accuracy will be lost ata time when it i s most important for the tracker to perform well.

This deficiency can beovercome by storing the state estimates and data points that extend for some time into themost recent past, say, mT seconds, where mT corresponds to the time delay in the responseof the detector to a maneuver. I f the maneuver is detected at time kT, then X^(k-m/k-m)gives the best estimate of the state based on measurements up to time (k-m) T that have notbeen significantly affected by the maneuver data . Then, using this estimate as startingpoint, a new track with (nearly) constant acceleration model is initialized and the track updated to time kT using the stored measurements y(k-m) , y(k-m+ l), ...y(k-l), y(k). thissince an estimate X^[k/Y(k),Y(k1).....Y(k-m) J which is the based is data which contains information that is relevant only to the maneuver and, hence, in some sense leads to anoptimal estimate. This is the tracker we have used in our simulations.

V. MANEUVER DETECTION

As one might expect, the discriminate that is used to detect the maneuver is the bias in the residual sequence. Therefore, as long as the target motion exactly coincides with the model upon which the tracking algorithm is based, then the residual sequence will continue to be a zero-mean, white noise process. Now, let us suppose that the target undergoes a maneuver. This can be modeled by the addition of an acceleration term to the dynamic equations which, in turn, manifests itself as an addition to the range, bearing and/or elevation measurements. Therefore, when a maneuver occurs, or if a non-linearity develops, i t manifests itself as a bias in the residual sequence. Thus, to detect the occurrence of the maneuver, it is necessary only to monitor the bias.

As long as no bias develops, we continue to use the straight line, constant-velocity tracker, when a bias is detected, then we would switch to a more general tracker that can better follow the maneuver.A simple fading memory average of innovations from the estimator based on the quiescentmodel is computed and used to detect if a maneuver has taken place as follows:

$\mu(k) = \Omega\mu(k-1) + \sigma\_0(k)$ (3.21)

With

$\sigma\_0(k) = nT(k)S-1(k)\,n(k)$ (3.22)

Where 0<Ω<1, n(k) innovation vector and S(k) is its covariance matrix.

Assuming n(k) is Gaussian distribution, σ_0(k) will have a chi-squared distribution with mdegrees of freedom where m is the dimension of the measurement vector(or m is the number of components of the state vector). It can be shown that the effective windowlength (h) of the fading memory average over which the presence of a maneuver is tested

is

$\Delta = (1 - \Omega) -1$ (3.23)

The procedure is illustrated as follows:

Accept the hypothesis that a maneuver is taking place if μ(k) exceeds a threshold whichcorresponds to a 95% confidence interval. Then the estimator switches from the quiescentmodel to the maneuvering model.Determine an end to a maneuver by similar logic. The fading memory average is kept during the maneuver to trigger the hypothesis test for a maneuver end. The hypotheses are:Ho, the maneuver has not ended; or Hn, the maneuver has ended at time (k-n). The hypothesis test, which is the same for maneuver detection, results in the measurement point (k-n) which is closest to the end of the maneuver. In a sharp turn, the velocity estimate at the point (k-n) may not be a good estimate of the actual non-maneuvering velocity., as shown in [5], another schemes for reverting to the quiescent model is asfollows: The estimated accelerations are compared to their standard deviation and if they are not statistically significant, the maneuver hypothesis is rejected

VI. SIMULATION RESULTS & DISCUSSION

In order to compare the estimates of the mentioned approaches, EKF and VDF, each of them is applied to estimate the following trajectory. In the scenario to be analyzed the target path is more severe for track management, and consists of five path legs:

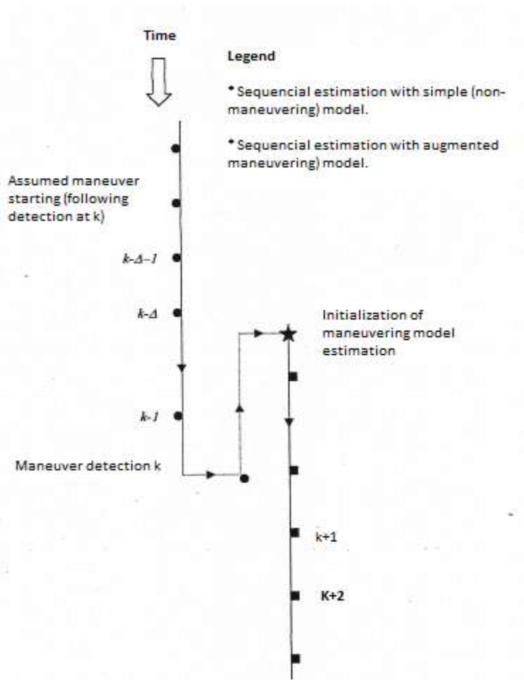

Fig.1 Switching from simple to augmented model

- A 250 m/s straight line path parallel to the x-axis.
- A brief 2.0 g 90 degrees turn maneuver.
- A straight-line path oriented parallel to y-axis.
- A 1.0 g 210 degrees pop-turn maneuver, and
- A straight-line path back toward the target starting point.

The projection of the trajectory on X-coordinate, Y-coordinate, Z-coordinate andon the 3-dimensional space x-y-z are as shown in figures (2&3). The trajectory begins at A = (50, 40, 3) Km. During the first 40s, the target travels along straight-line path parallel to x-axis at constant speed (250 m/s). From B to C, it turns 90 degrees with a centrifugal acceleration of 2.0g (19.6 m/s2). It completes the turn at t = 60 seconds. From C to D, until time 107s it travels again a straight-line path oriented parallel to the y-axis with a constant speed (250 m/s). From D to E the second pop-turn, of1.0g and 210 degrees, occurs and is completed at time 160.6 s (altitude is changed from 3 to 4 Km, after approximately 53s. After that, it travels astraight-line path back toward the target starting point until time 200s.

The radar is located at the origin. It scans at 60rpm, which yield a sampling of ls. The radar polar coordinates r,θT , and θE are originate at he radar. r is the range from the radar to the aircraft, θT is the azimuth angle (measured positive from the north clockwise), and θE is the elevation angle (measured positive upward from horizontal). The measurement noises in range, azimuth and elevation are white Gaussian with zero means, and standard deviations of σR = 30 m and $\sigma_{\theta T} = \sigma_{\theta E}$ =3mrad. The standard deviation of the random acceleration due to the normal atmospheric disturbances is assumed to be 10 m/s2, and its acceleration time constant is 1/α = 10 s. Target trajectory noise simulation on each coordinate are as shown in fig (4).
The results of the EKF and VDF calculations are presented in Fig (5 - 16).

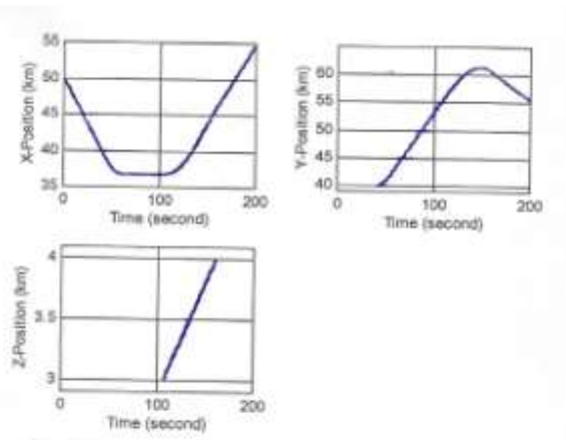

Fig.2 Projection of the trajectory on each coordinate (x,y,z)

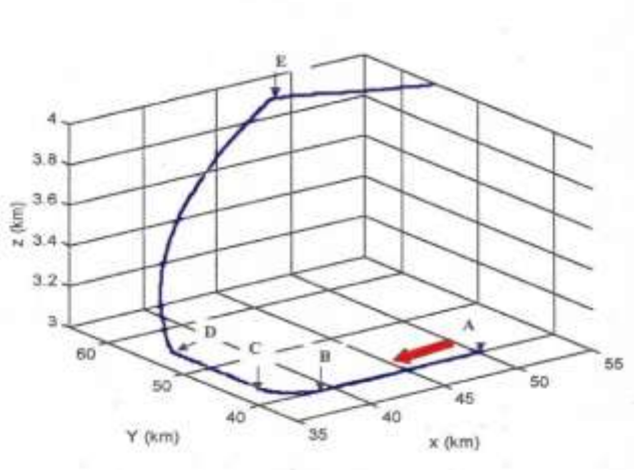

Fig.3, 3-Dimensional Space Target Motion

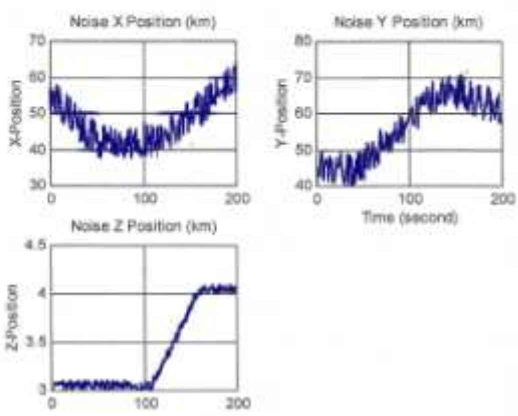

Fig.4 , Projection of the target trajectory noise simulation on each coordinate(x,y,z)

In figures (5 - 6 - 7) the RMS errors in position are plotted in each direction (x, y,z) . itseen that the two trackers appear to be equally effective during the maneuveringperiod , while in the constant course of the target trajectories, the **VDF** has a lower averageerror than the EKF. The computation requirements for the VDF were about three timeslower than for the EKF based on the running time of our simulations. In view of the RMSerror and computation requirements, one can state that the VD algorithm is superior to theEKF algorithm.Figure (8) gives the parametric behavior of the ratio $p(1,1)/R_{11}$ which is the ratio of the variance of the steady-state error in filtered position to the transformed variance of the single-look sensor observation noise. This ratio represents the improvement in position tracking resulting from using the optimal filter rather than the raw sensor measurements directly. When this ratio is closed to unity, the accuracy improvement provided by the filter is small. As the ratio decreases toward zero, the filter becomes increasingly effective.

Figure (9) gives the parametric behavior of the ratio $p(4,4)/R_{11}$ the ratio of the varianceof the steady-state error in filtered speed along the x-dimension to the variance of theobservation noise in that dimension.

Figure (10) gives the parametric behavior of the ratio $p(7,7)/R_{11}$ but their utility is small compared to those shown in figures (8) and (9).These three figures (8 - 10) can be extremely useful for providing a quick, first-cut estimate of the tracking performance for any system in which the sensor provides some combination of range, bearing and elevation data. Also from these figures we have deduced that the tracking accuracies obtained with a VDF algorithm is superior to the EKF algorithm except through switching, large transient errors occur during filter switch.In figures {11-13) the residual errors (y(k)-h(x^(k/k-1))) between the estimated statevectors, expressed in radar coordinates, and the data are plotted. It is well known that ifboth the system model and noise statistic are true representations of the actual physical process, the filter innovation process for non-linear system [γ_k =y (k)-h(x^(k/k-l))], appear to be a close approximation and is white Gaussian with zero mean and covariance [$P\gamma_k = H(k)\, P\gamma_k(k/k-1) H^T(k) + R(k)$] and the filter achieves optimal performance.If the test indicates that the filter does not attain optimal performance, one then proceedsto adjust Q and R so that the covariance of the innovation process will be consistent withthat of filter prediction.

We emphasize that the concept presented above is important because it indicates that systematic procedures for identifying the noise covariance or filter gain can be established.

It may not be very useful for real-time applications because of its computational requirement For non-real-time application, however, this method is useful for simulations and post mission data analysis studies. The identification of divergence in filter operation can often be obtained by examining the statistics of the term y(k)-h(x^(k/k-l) so-called innovations process which should be a zero mean white noise process. Or, the estimation error covariance matrix can be monitored to determine if the diagonal elements tend toward zero with increasing time. We see that correct choice of Q and R reduce performance sensitivities to model errors and preventing filter divergence.

In figures (14-16) we have plotted the corrections (x^(k/k)-x^(k/k-1)) applied to the estimated state vector at each observation (where x (k/k) is the estimated state vector after y(k) has been processed) and x^(k/k-1) is the predicted state estimate for each observation y(k) . It is obvious from these figures that the filter generated estimates are unbiased during the constant course of the target trajectories, while the bias induced due to the maneuver occur is rapidly decrease due to the correction procedure and the filter convergent to the steady-state. We see also from the figures, that the filter gain provides the weighting of the update procedure. When the filter gain is very small, the estimator
becomes insensitive to the new measurements and this may result in large bias errors.

When the filter gain is very large, the estimator is deem phasing past measurements, possibly resulting in large random error. A balance can be achieved if one has sufficient knowledge regarding the accuracy of the state model and the measurement process.

From the forgoing analysis and simulation studies, it is worth to mention the following observations:

- For non-linear system VDF gives a better estimate than that of the EKF weather, thesystem model is noise free(Q = 0)or not.
- If the objective of tracking is to obtain precision information about the target dynamics, then one should use the most accurate model and apply the EKF or VDF. If the dynamic model is sufficiently accurate so that the process noise term is negligible, then the VDF algorithm is a good choice provided that the computation time and data storage requirement are not excessive.
- If the objective is just to maintain the target in track, then one may use the simplest track algorithm such as the least square filters. *One* exception to this case is when tracking in a dense target environment or tracking maneuvering target, where precision tracking may be necessary for target correlation and prevent lose of track.
- The maneuver detection relies on the fact that target maneuvering generates residual bias in a non-maneuvering tracker. Once the filter is switched to maneuvering model, another scheme can be used to discriminate if the target has ended the maneuver.
- Using a detector - directed tracking include:

- Detection delay.
- Large transient errors during filter switch.
-Storage and processing time requirement for a large batch of past measurements.

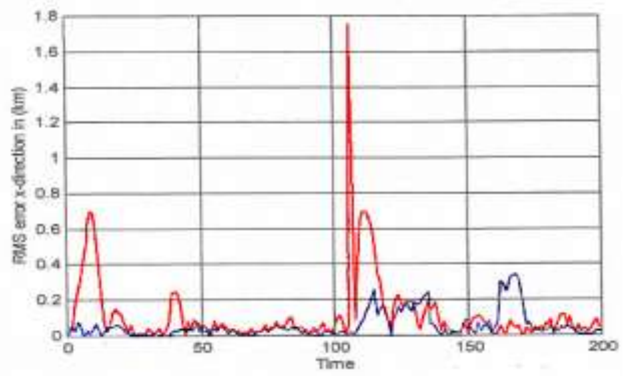

Fig.5 , RMS Estimation in X-position for EKF , VDEKF

EKF VDEKF

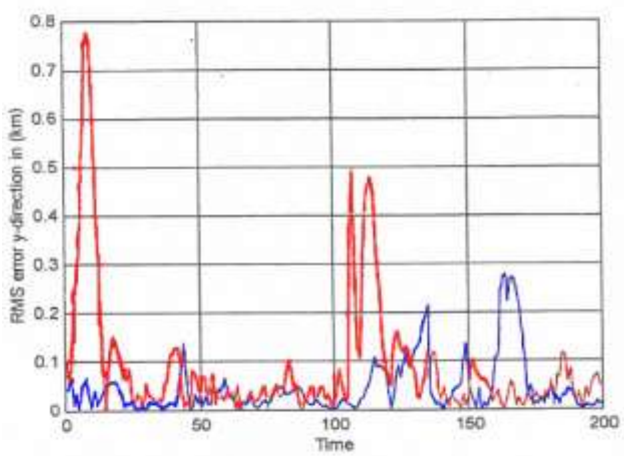

Fig.6 , RMS Estimation in y- position for EKF , VDEKF

EKF VDEKF

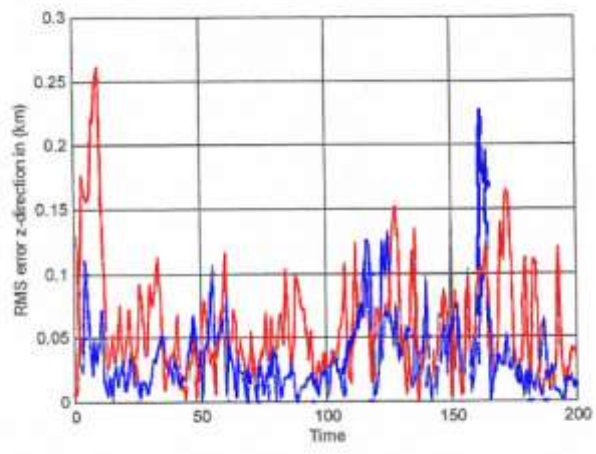

Fig. 7, RMS Estimation in z- position for EKF, VDEKF

EKF VDEKF

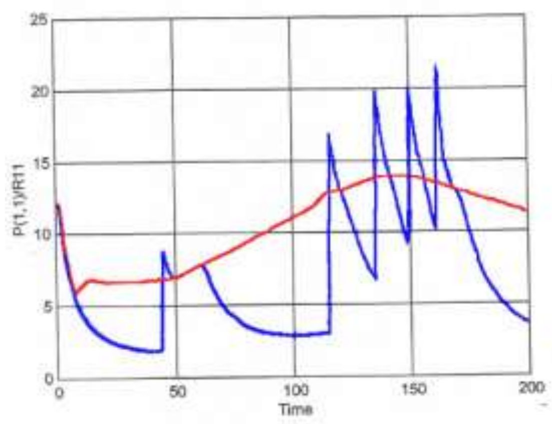

Fig.8 , Parametric behavior of the ratio P(1,1)/ R_{11}

EKF VDEKF

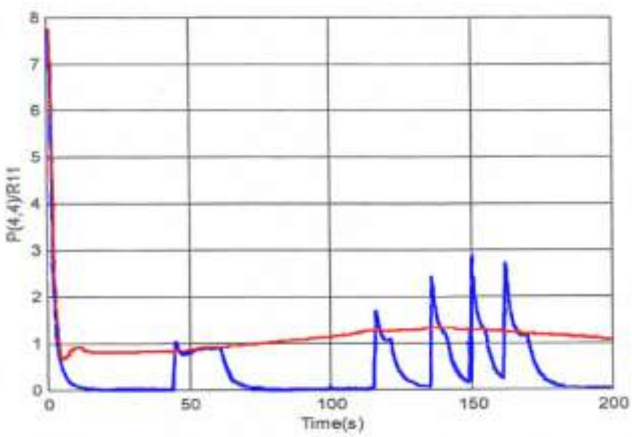

Fig.9 , Parametric behavior of the ratio P (4,4)/ R_{11} for EKF , VDEKF

EKF VDEKF

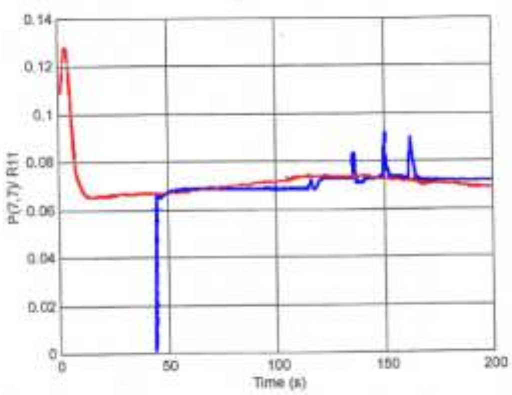

Fig.10, Parametric behavior of the ratio P(7,7)/R_{11} for EKF , VDEKF

EKF VDEKF

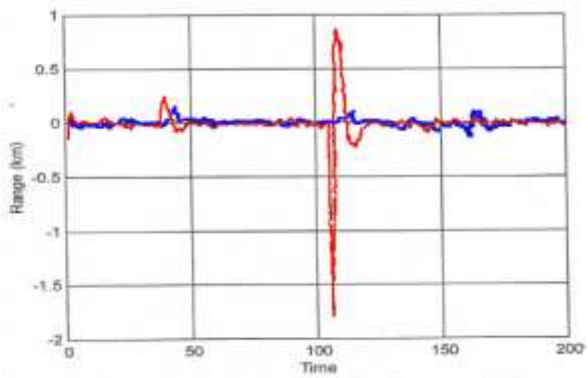

Fig.11 Residual error in range for EKF , VDEKF

EKF VDEKF

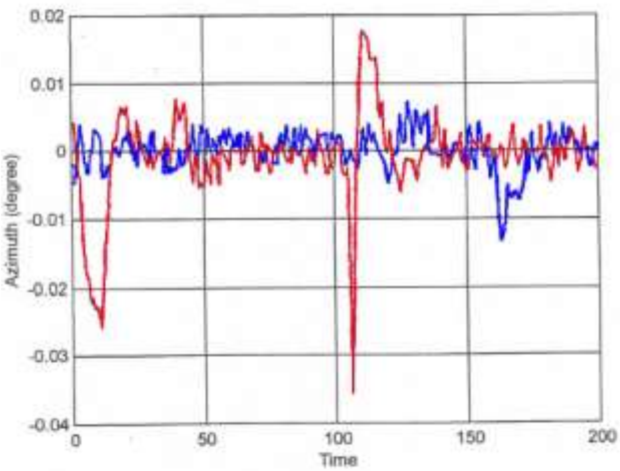

Fig.12 , Residual error in azimuth for EKF, VDEKF

EKF VDEKF

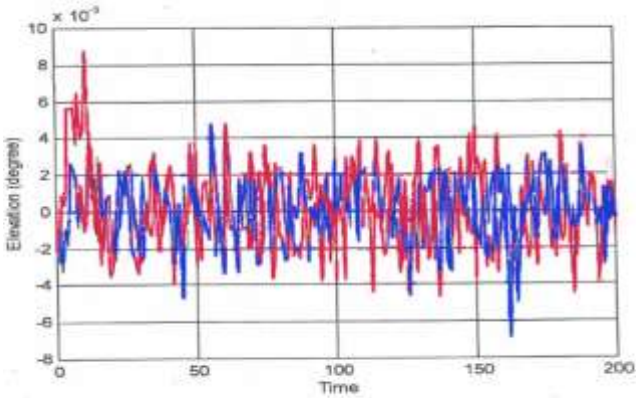

Fig.13, Residual error in elevation for EKF , VDEKF

EKF VDEKF

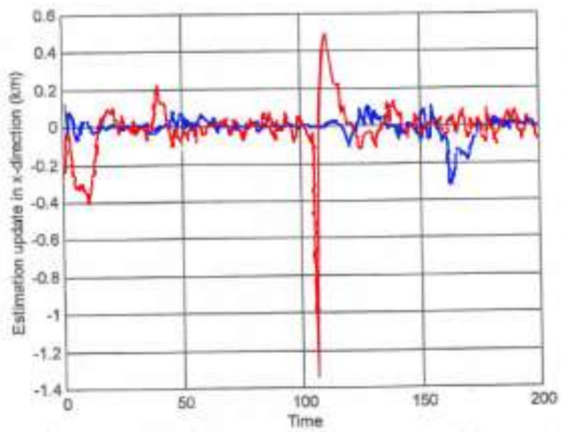

Fig.14, EKF & VDEKF estimation update for position in x- direction

EKF VDEKF

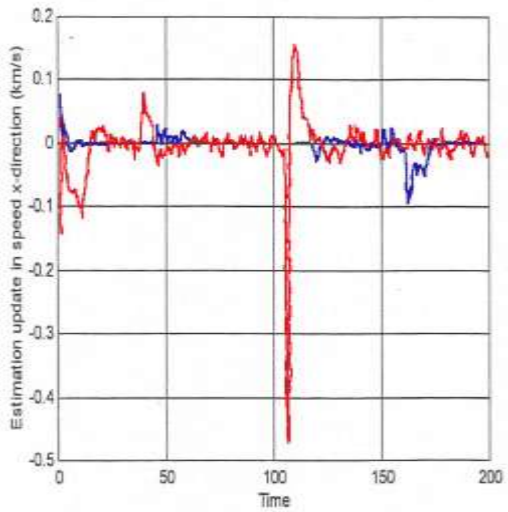

Fig.15, EKF & VDEKF estimation update for speed in y- direction

EKF VDEKF

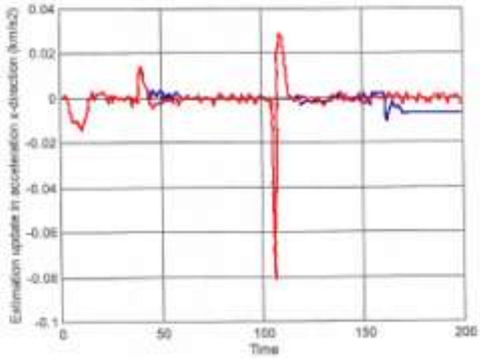

Fig.16, EKF & VDEKF estimation update for acceleration in x- direction

EKF VDEKF

VII. CONCLUSION

The generalized tracker EKF suffers during the straight-line motion Rom loosing accuracy due to the fact that it always tracks with a state vector consisting of position, velocity and acceleration. While in the VDF initially the acceleration is set to zero along with it variance so that the filter is tracking as if the state vector only-had position and velocity. After a maneuver is detected the **VDF** keeps the acceleration in the process model. The detector requires a minimum amount of computation and memory the filter remain in itsnormal mode (constant velocity) for most of the time and goes to the augmented modelonly when it detects that maneuvering has tacking place. The scheme is simple in concept and the computational load is very low. Hence it is reel-time implementable. The VDFdoesn't have a large transient due to the fact that the VDF doesn't estimate when the maneuver occurred. The **VDF** assumes that the maneuver occurred a fixed time before maneuver detection. This results in an earlier detection of maneuver but suffers from a longer transient response, after an initial transient at the start of the maneuver the VDF continues to improve its estimate of the position. Finally in the next chapter, it will be seen that the performance of EKF and **VDF** in particular cases can be improved by using a new filtering algorithms called Gaussian second-order filter and Iterative filter.

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