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Adaptive Estimation of Line-of-sight Rate Measurement from a Radio Frequency Seeker

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ABSTRACT

The line-of-sight (LOS) rate output from a radio frequency (RF) seeker is widely used during the homing phase guidance of a tactical missile. The LOS rate is noisy and needs to be filtered. The application of an adaptive Kalman filter for the LOS rate state estimation has been studied. This filter requires minimal *a priori* knowledge about technical parameters of the seeker. It is also capable of estimating the variable noise statistics.

Keywords: RF seeker, missile guidance, miss-distance, guidance, control, line-of-sight rate measurement, LOS rate estimation, tactical missile, guidance command computation, homing phase guidance

NOMENCLATURE

$\dot{\lambda}_{el}$	LOS rate (elevation)
$\dot{\lambda}_{az}$	LOS rate (azimuth)
ϕ	State transition matrix
$\hat{P}_k$	Updated error covariance
$\hat{R}_k$	Estimated measurement noise covariance
r_k	Innovation
$\hat{r}_k$	Estimated noise mean
$\hat{Q}_k$	Process noise covariance

1. INTRODUCTION

The radio frequency (RF) seekers are widely used to measure the target-interceptor relative state during the terminal homing phase for guidance purpose. Figure 1 shows a typical interceptor guidance system in the form of a control loop. The line-of-sight (LOS) rate output from the RF seeker is used for guidance command computation. From among the contributors to miss-distance[1], the noise on the seeker-measured variables is prominent. The seeker measures the LOS rate, range rate and gimbal angles, which are used for the interception. These measurements are noisy and need to be filtered. The major noise components in the LOS rate are from the seeker receiver, target glint, and the eclipsing

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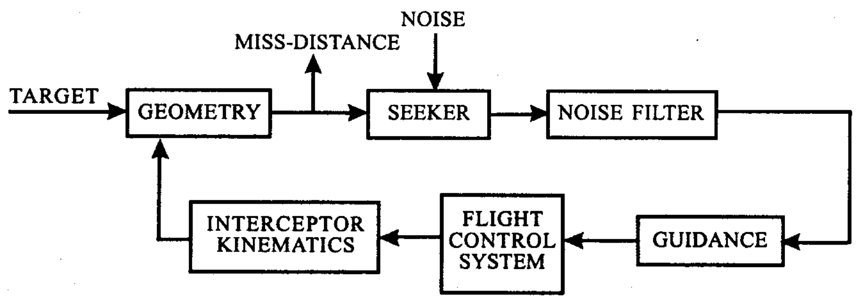

Figure 1. Interceptor guidance system

phenomenon, out of which the range-dependent receiver noise is dominant[2]. The basic LOS signal characteristics depend upon the intercept geometry. It is, therefore, necessary to estimate the important guidance input, namely the LOS rate, without vitiating the basic signal characteristics[3].

A Kalman filter can be used to estimate the noisy seeker measurements. Besides, it can provide estimation of higher derivatives of the LOS rate[4] for minimising the miss-distance. The noise statistics of the seeker measurements are unknown during the flight. An adaptive discrete Kalman filter is thus well-suited for the seeker state estimation where the noise statistics is unknown. A noise modelling approach[3] can be used for generating the measurement noise statistics. However, this can't model the eclipsing phenomenon exactly as it would occur during the flight. Besides, the noise modelling approach requires extensive technical data of seeker internals and accurate "time to go" estimation. A two-state observer approach is also reported for the LOS estimation[5].

This study contains application of an adaptive discrete Kalman filter for the LOS rate estimation in the presence of unknown measurement noise. The filtering was also tested in an intercept simulation.

2. FILTER CONFIGURATION

The adaptive discrete Kalman filter is configured to estimate the $\dot{\lambda}$ and $\ddot{\lambda}$. The LOS rate output available from an RF seeker ($\dot{\lambda}$) is taken as the measurement. The filter consists of azimuth and elevation channels. The filtering is done in the same frame as that of the seeker output. Figure 2 shows a context diagram of the seeker filtering (Rk_{el}, Rk_{az} are the estimates of measurement noise).

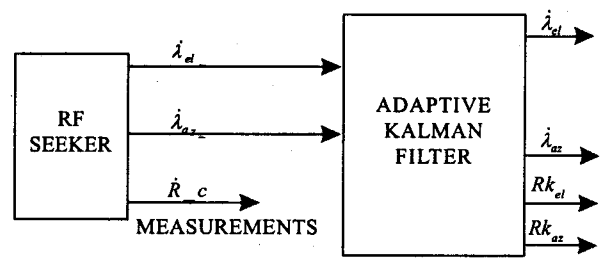

Figure 2. A context diagram of a seeker filtering

3. STATE MODEL & ADAPTIVE FILTERING ALGORITHM

The state model uses the linear combination of the time derivatives of the LOS rate ($\dot{\lambda}$). It is a series approximation to the function. The state model has two higher derivatives of $\dot{\lambda}$.The term $\ddot{\lambda}$ is taken into the model to account for the slope changes that are possible in an encounter with a manoeuvreing target. The filtering algorithm used is based on the one proposed by Myers and Tapley[6]. This adaptive filtering algorithm is well-suited in the cases where the measurement noise statistics is variable and unknown. A non-adaptive filter requires knowledge of the variation of noise statistics as a function of range to work. It is, therefore, advantageous to use an adaptive Kalman filter if the noise variation pattern is unknown. The algorithm uses only the measurement noise estimation. The process noise estimation is not used. Instead, the process noise is kept constant and tuned for better filter performance.

4. ALGORITHM

- *State & Covariance Propagation*

States: $\dot{\lambda}\ \ddot{\lambda}\ \dddot{\lambda}$

(a) $\tilde{X}_k = \phi_k \hat{X}_{k-1} + \hat{q}_{k-1}$

where

$$\phi = \begin{bmatrix} 1 & dt & 1/2dt^2 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix}$$

$$dt = t_k - t_{k-1}$$

(b) $\tilde{P}_k = \phi_k \hat{P}_{k-1} \phi_k^T + \hat{Q}_{k-1}$

$$r_k = y_k - H_k \tilde{X}_k$$
$$\gamma_k = H_k \tilde{P}_k H_k^T$$
$$\hat{r}_k = \hat{r}_{k-1} + 1/lr(r_k - r_{k-lr})$$

$$\hat{R}_k = \hat{R}_{k-1} + 1/(lr-1)\{(r_k - \hat{r}_k)^2 - (r_{k-lr} - \hat{r}_k)^2 + 1/lr(r_k - r_{k-lr})^2 + ((lr-1)/lr)(\gamma_{k-lr} - \gamma_k)\}$$

- *Compute Kalman Gain*

$$K_k = \tilde{P}_k H_K^T [\gamma_k + \hat{R}_k]^{-1}$$

- *State & Covariance Updates*

$$\hat{X}_k = \tilde{X}_k + K_k[r_k + \hat{r}_k]$$

$$\hat{P}_k = \tilde{P}_k - K_k H_k \tilde{P}_k = (I - K_k H_k)\tilde{P}_k$$

- *Compute State Noise*

$$q_k = \hat{X}_k - \phi_k \hat{X}_{k-1}$$
$$\Delta k = \phi_k \hat{P}_{k-1} \phi_k^T \dot{\hat{P}}_k$$
$$\hat{q}_k = \hat{q}_{k-1} + 1/lq(q_k - q_{k-lq})$$

$$\hat{Q}_k = \hat{Q}_{k-1} + 1/(lq-1)\{(q_k - \hat{q}_k)^2 - (q_{k-lq} - \hat{q}_k)^2 + 1/lq(q_k - q_{k-lq})^2 + ((lq-1)/lq)[\Delta_{k-lq} - \Delta_k]\}$$

5. TEST CASES & RESULTS

Test Case 1

Simulated Data (Constant Gaussian Noise)

Initially, the filter performance is checked using simulated noisy data in azimuth and elevation channels. The zero mean Gaussian noise is used for corrupting the true data. The noise variance is kept constant. The results are shown as follows:

Description	Figure Nos
LOS rate error plots (filtered and true)	3 and 4
Estimation of constant measurement noise	5
Estimation of LOS rate and its derivative	6 and 7
Residue and estimated noise mean	8

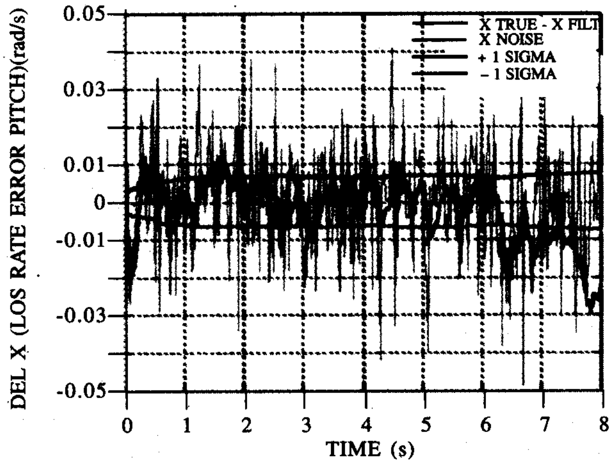

Figure 3. Estimation of seeker states and noise using an adaptive Kalman filter. The LOS rate error(pitch) plots (filtered and true).

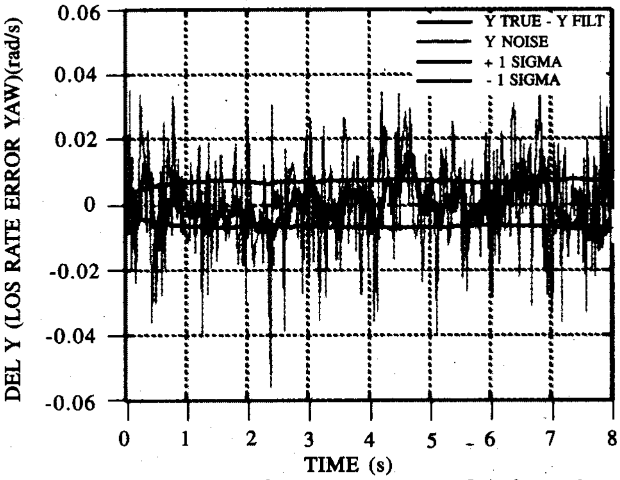

Figure 4. Estimation of seeker states and noise using an adaptive Kalman filter. The LOS rate error(yaw) plots (filtered and true).

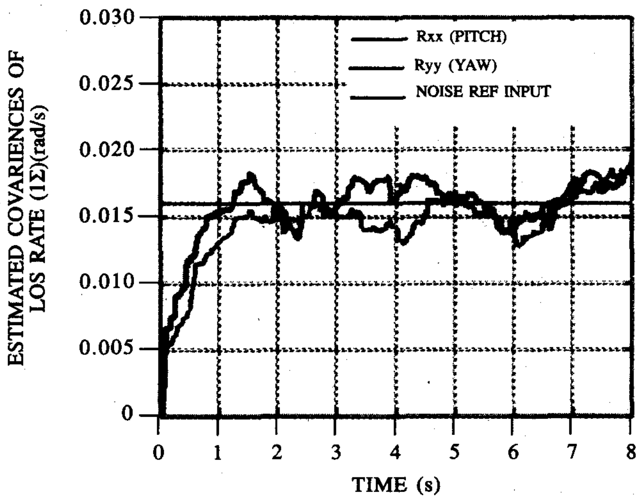

Figure 5. Estimation of seeker states and noise using an adaptive Kalman filter. Estimation of constant measurement noise.

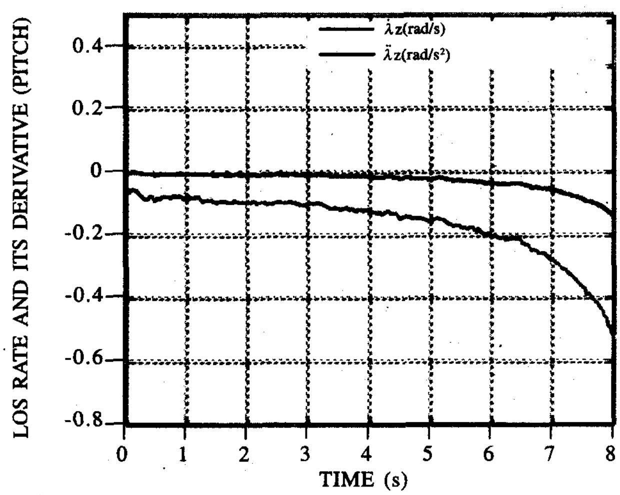

Figure 6. Estimation of seeker states and noise using an adaptive Kalman filter. Estimation of LOS rate and its derivative (pitch).

Test Case 2

Data from Stand-alone Seeker Mathematical Model

The data is generated from an elaborate seeker mathematical model for an RF seeker. The mathematical model takes into account the receiver noise, target glint, and eclipsing effects. The data corresponds to an engagement simulation. The results are shown as follows:

Description	Figure Nos
LOS rate error plots (filtered – true)	9 and 10
Estimation of variable measurement noise	11

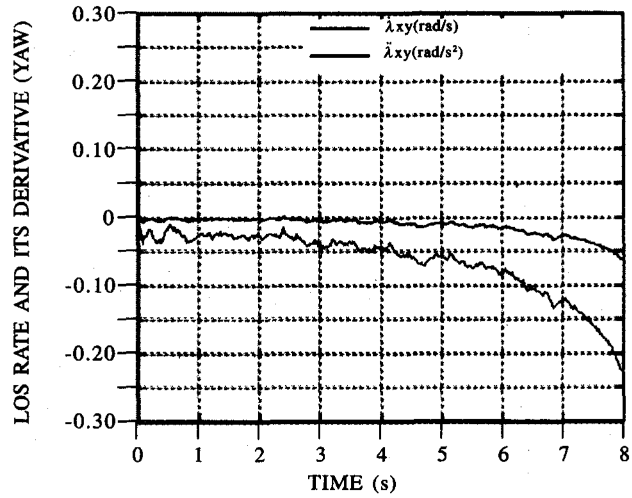

Figure 7. Estimation of seeker states and noise using an adaptive Kalman filter. Estimation of LOS rate and its derivative (yaw).

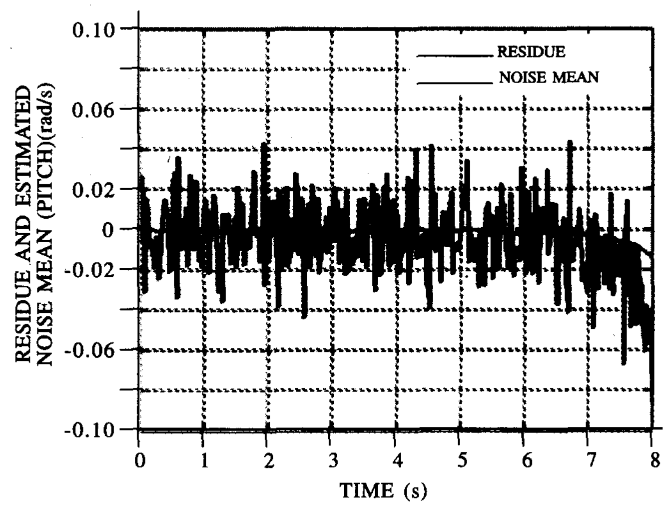

Figure 8. Estimation of seeker states and noise using an adaptive Kalman filter. Residue and estimated noise mean (pitch).

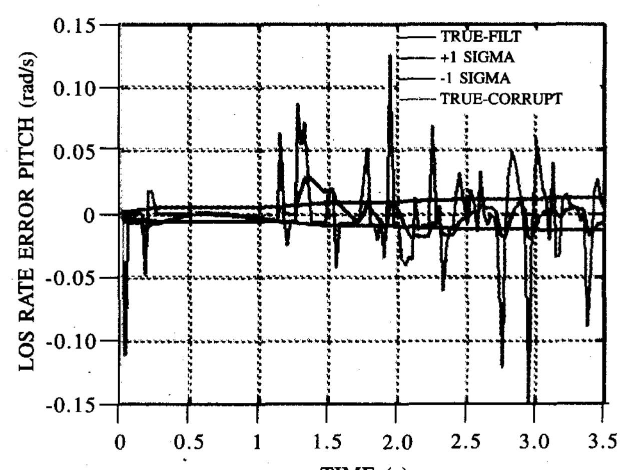

Figure 9. Estimation of seeker state using an adaptive Kalman filter. The LOS rate error pitch (filtered and true).

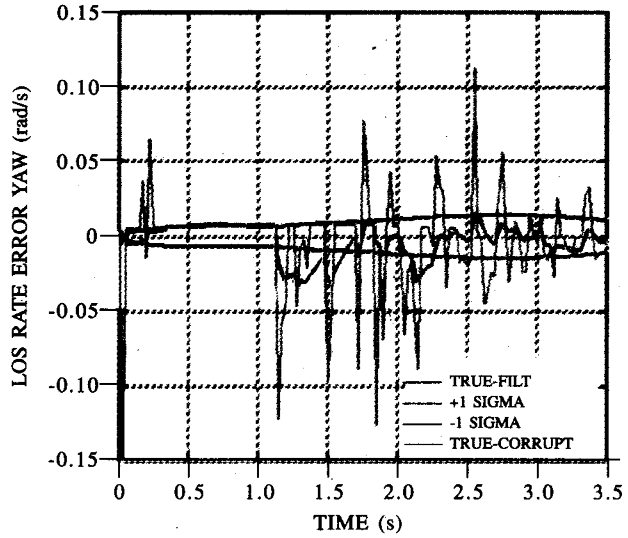

Figure 10. Estimation of seeker state using an adaptive Kalman filter. The LOS rate error pitch (filtered and true).

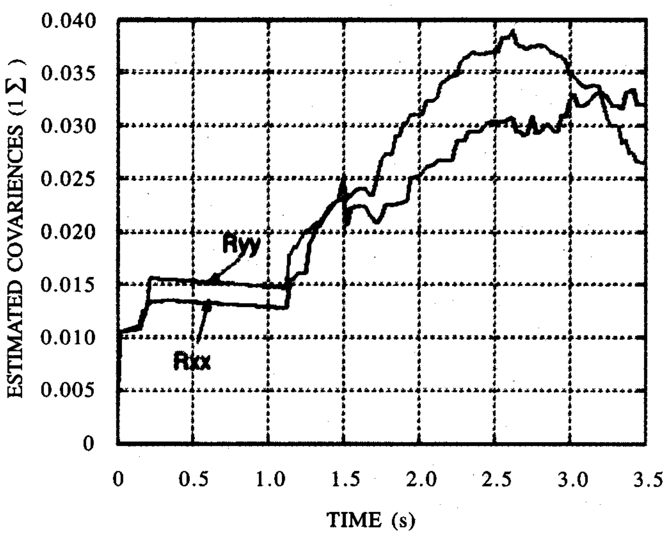

Figure 11. Estimation of seeker state using an adaptive Kalman filter. Estimation of variable measurement noise.

Test Case 3

Intercept Simulation

The effect of filtering is studied in an exoatmospheric intercept simulation. Figure 12 shows that the miss-distance improves by an order due to the filter. Figure 13 shows that the control effort is less when the filter is used.

6. CONCLUSION

The LOS rate state estimator based on adaptive Kalman filter is developed and tested. The state

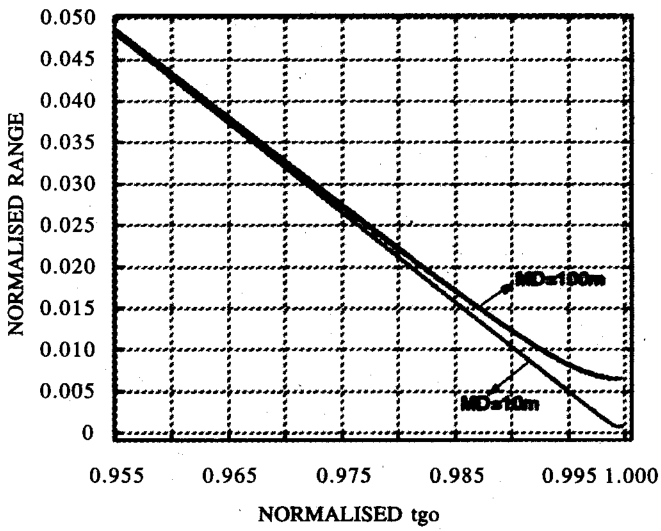

Figure 12. Missile-to-target range

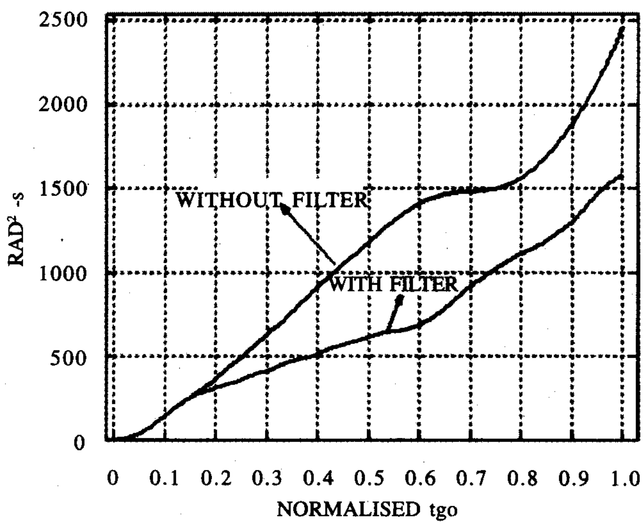

Figure 13. Total control effort

model consists of time series approximation of the function . A coupled formulation is used while forming the state transition matrix comprising azimuth and elevation channels.

The filter performance in terms of estimation error and measurement noise computation is adequate. The estimation of $\dot{\lambda}$ and $\ddot{\lambda}$ is found to be satisfactory. The filter requires no *a priori* information, and is capable of estimating variable measurement noise.

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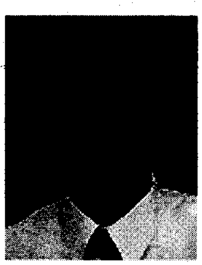

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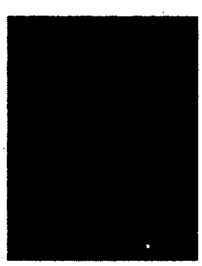

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