

Definitions:

- x : process model states
- ϕ : state-transition matrix
- H : measurement matrix
- z : measurement matrix
- \hat{x}_0^- : initial conditions of states
- P_o^- : initial error covariance matrix
- R : variance of measurement error matrix
- Q : variance of process model noise
- λ : forgetting factor $0 < \lambda < 2$
- λ^* : initial forgetting factor

Notations:

- $\hat{\cdot}$: estimate
- \hat{x}_k^- : a prior estimate of x_k
- \hat{x}_k^+ : a posterior estimate of x_k

Discrete Kalman Filter:

1. Guess initial values of P_0^- and \hat{x}_0^-
2. Calculate the gain :
 - $K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$
3. Update estimate :
 - $\hat{x}_k^+ = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-)$
4. Update error :
 - $P_k^+ = (I - K_k H) P_k^-$
5. Project ahead :
 - $\hat{x}_{k+1}^- = \phi \hat{x}_k^+$
 - $P_{k+1}^- = \phi P_k^+ \phi^T + Q$
 - $P_{k+1}^- = \frac{P_{k+1}^- + P_{k+1}^{-T}}{2}$

Discrete Kalman Filter with Forgetting Factor λ :

1. Guess initial values of P_0^- and \hat{x}_0^-
2. Calculate the gain :
 - $K_k = P_k^- H^T (H P_k^- H^T + R\lambda)^{-1}$
3. Update estimate :
 - $\hat{x}_k^+ = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-)$
4. Update error :
 - $P_k^+ = (I - K_k H) \frac{P_k^-}{\lambda}$
5. Project ahead :
 - $\hat{x}_{k+1}^- = \phi \hat{x}_k^+$
 - $P_{k+1}^- = \phi P_k^+ \phi^T + Q$
 - $P_{k+1}^- = \frac{P_{k+1}^- + P_{k+1}^{-T}}{2}$

Discrete Kalman Filter with Varying Forgetting Factor λ :

1. Guess initial values of P_0^- , \hat{x}_0^- and λ^*

2. Calculate the gain :

$$\bullet K_k = P_k^- H^T (H P_k^- H^T + R \lambda_k)^{-1}$$

3. Update estimate :

$$\bullet \hat{x}_k^+ = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-)$$

4. Update error :

$$\bullet P_k^+ = (I - K_k H) \frac{P_k^-}{\lambda_k}$$

5. Project ahead :

$$\bullet \hat{x}_{k+1}^- = \phi \hat{x}_k^+$$

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

$$\bullet P_{k+1}^- = \frac{P_{k+1}^- + P_{k+1}^{-T}}{2}$$

6. Forgetting factor λ :

$$\bullet \epsilon = (z_k - H \hat{x}_k^+)$$

$$\bullet \lambda_{k+1} = 1 - \frac{(1 - \hat{x}_k^{+T} K_k) \epsilon^2}{\sigma^2(\epsilon) \mu(\epsilon)}$$

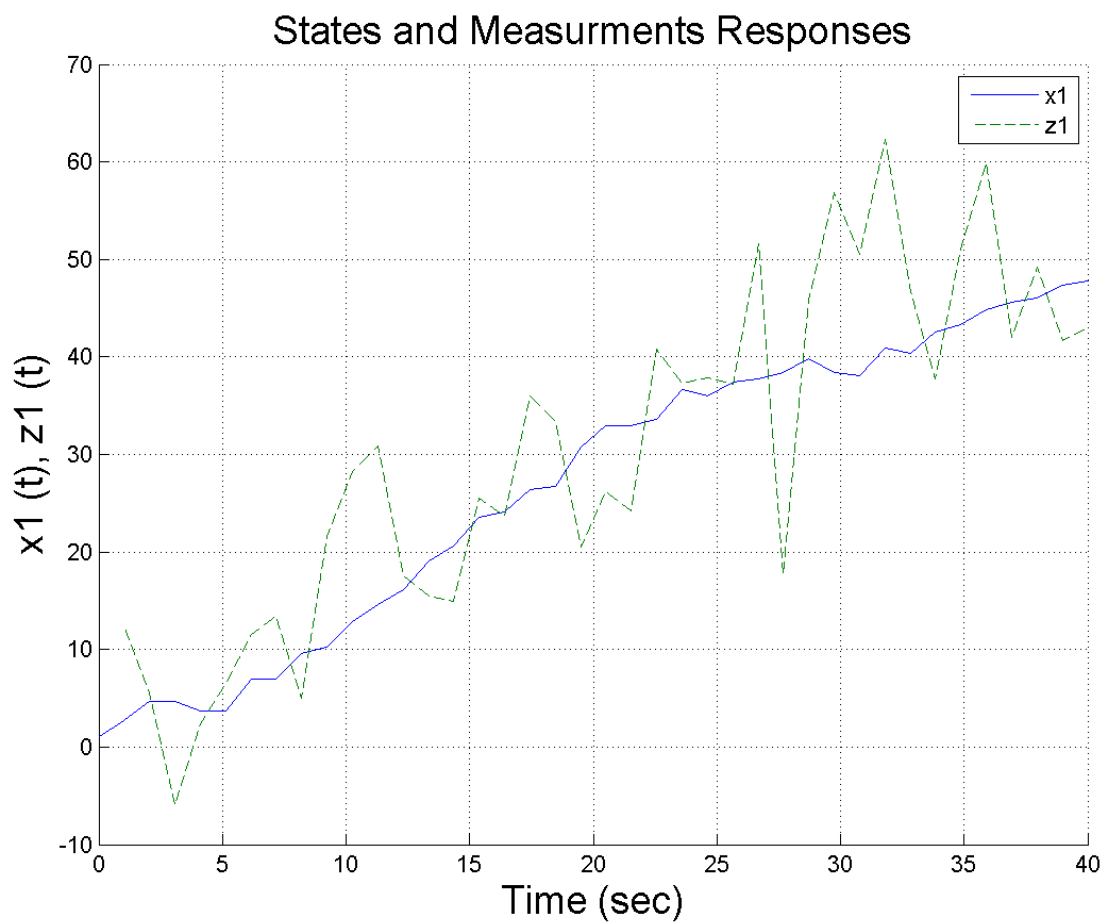
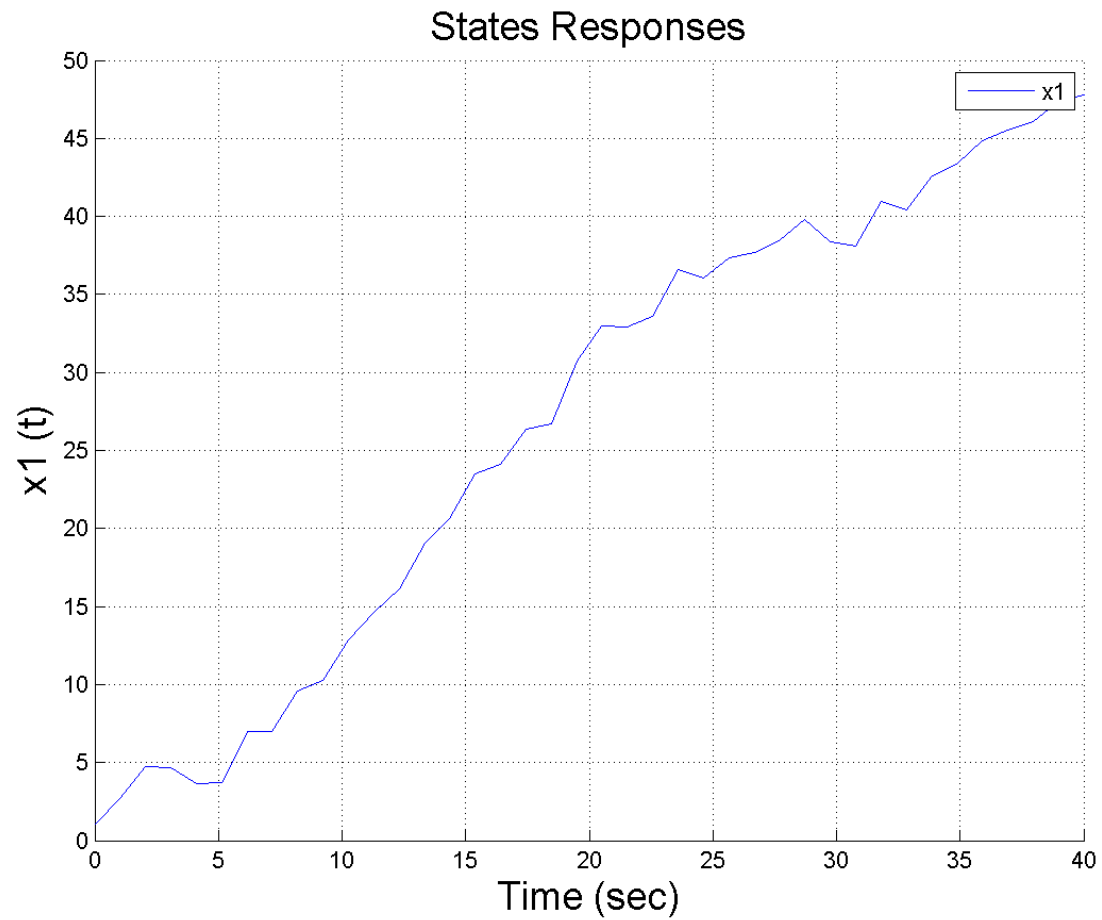
$$\bullet \lambda_{k+1} = \begin{cases} > 0.95 & \lambda_{k+1} = 0.95 \\ < 0.3 & \lambda_{k+1} = 0.3 \\ else & \lambda_{k+1} = \lambda_{k+1} \end{cases}$$

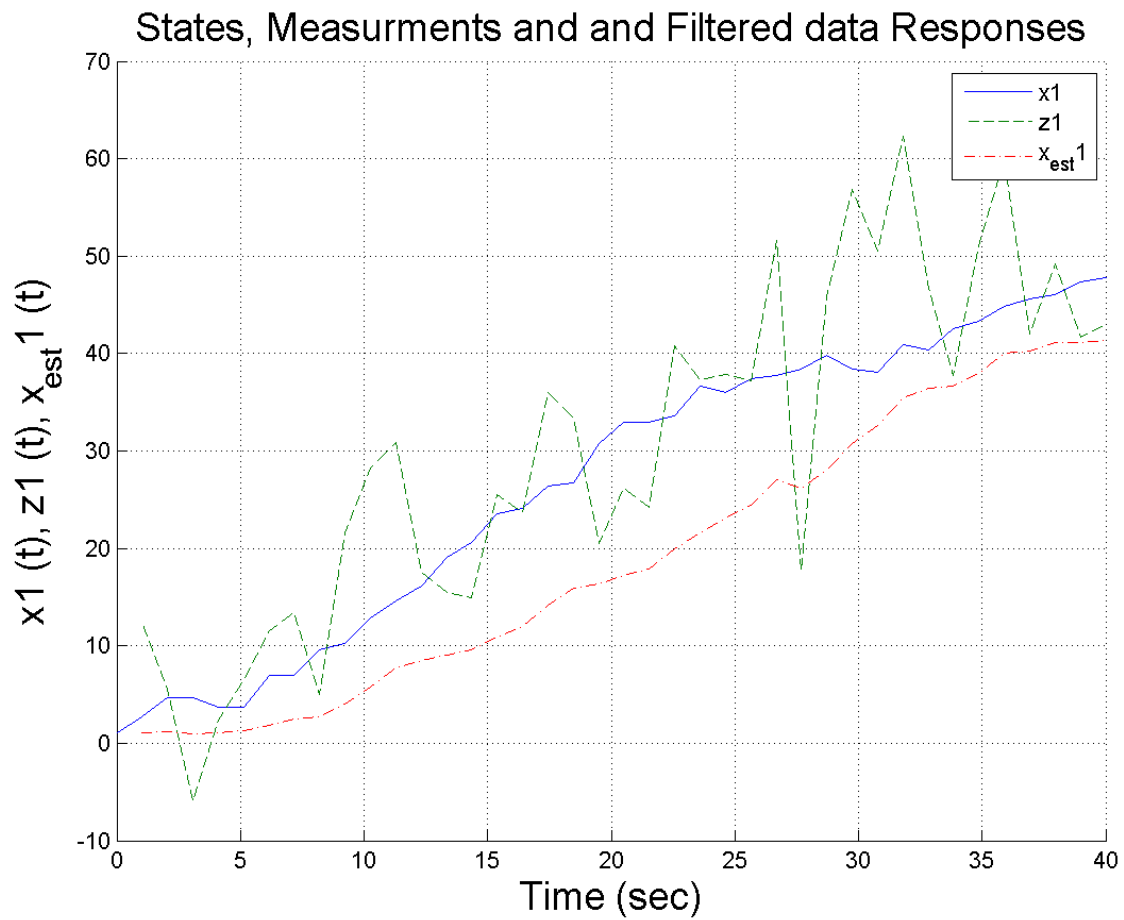
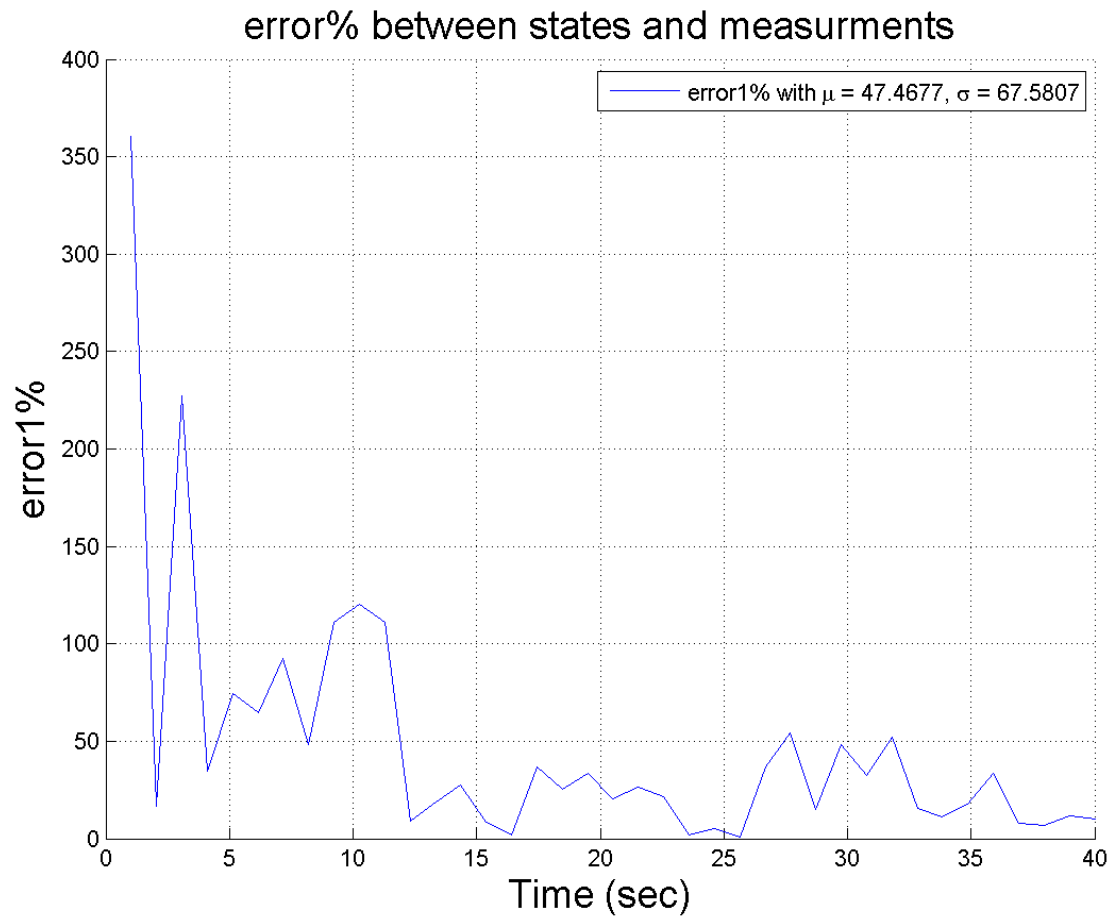
Example:

- $\phi = 1$
- $H = 1$
- $R = 100$
- $Q = 1$
- $\hat{x}_0^- = 1$
- $P_0^- = 0$
- $\Delta t = 1.0256$
- $x(1) = 1$
- $x(k+1) = \phi x(k) + \Delta t + \text{normrnd}(0, \sqrt{Q})$
- $z(k) = H x(k) + \text{normrnd}(0, \sqrt{R})$
- $\lambda = 0.9$
- $\lambda^* = 0.9$

Results :

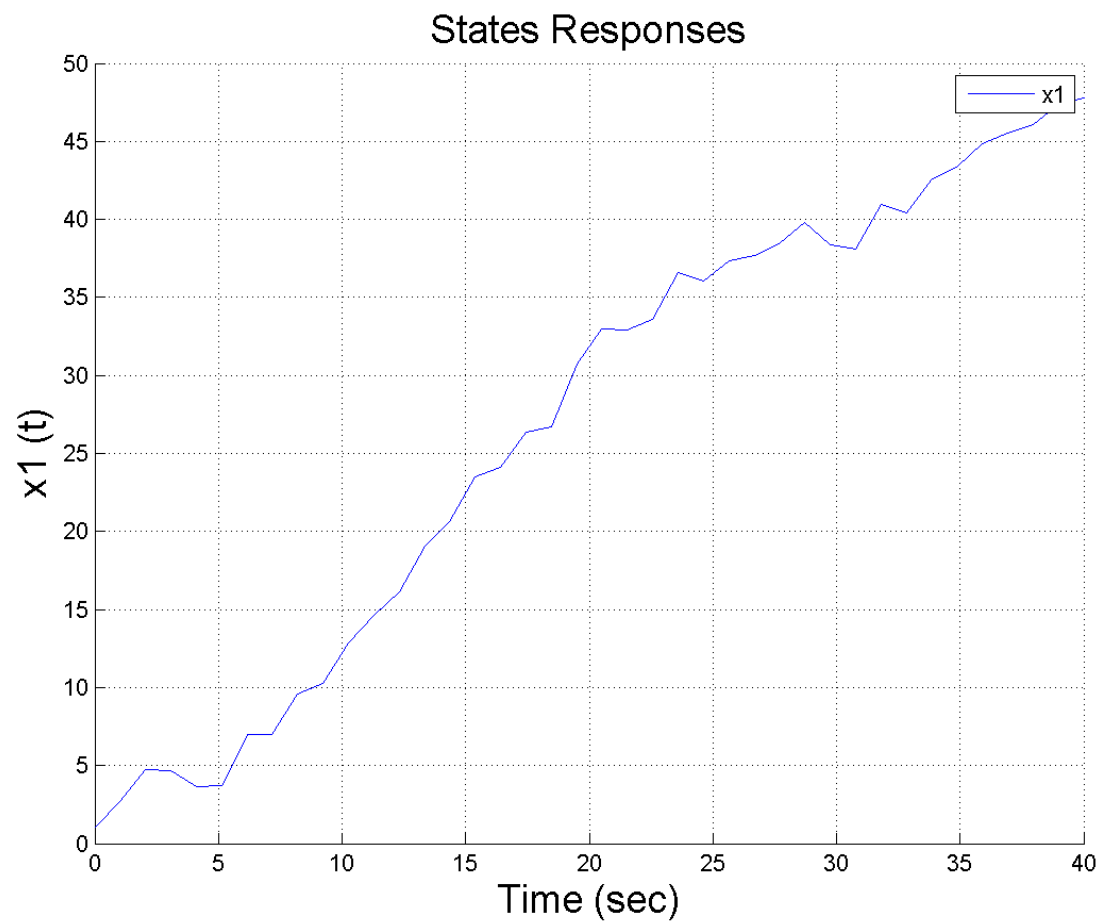
Discrete Kalman Filter:

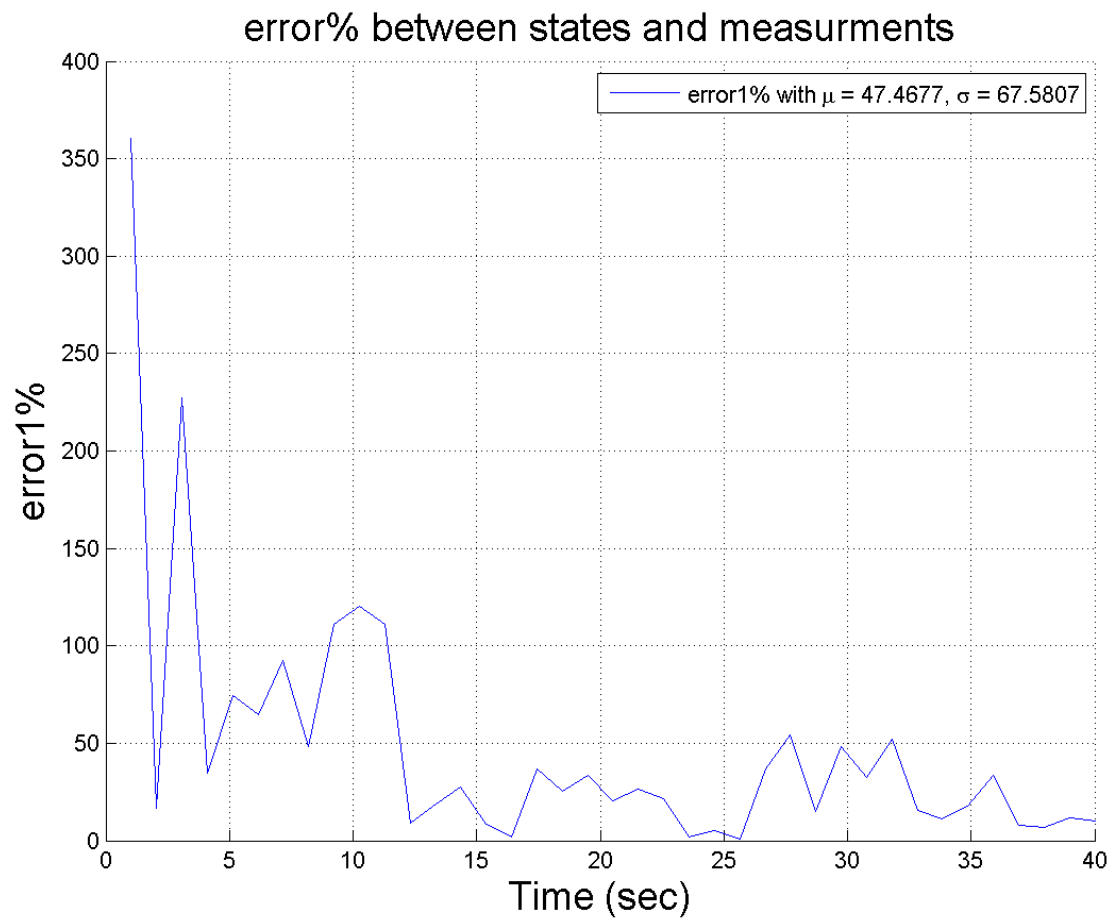
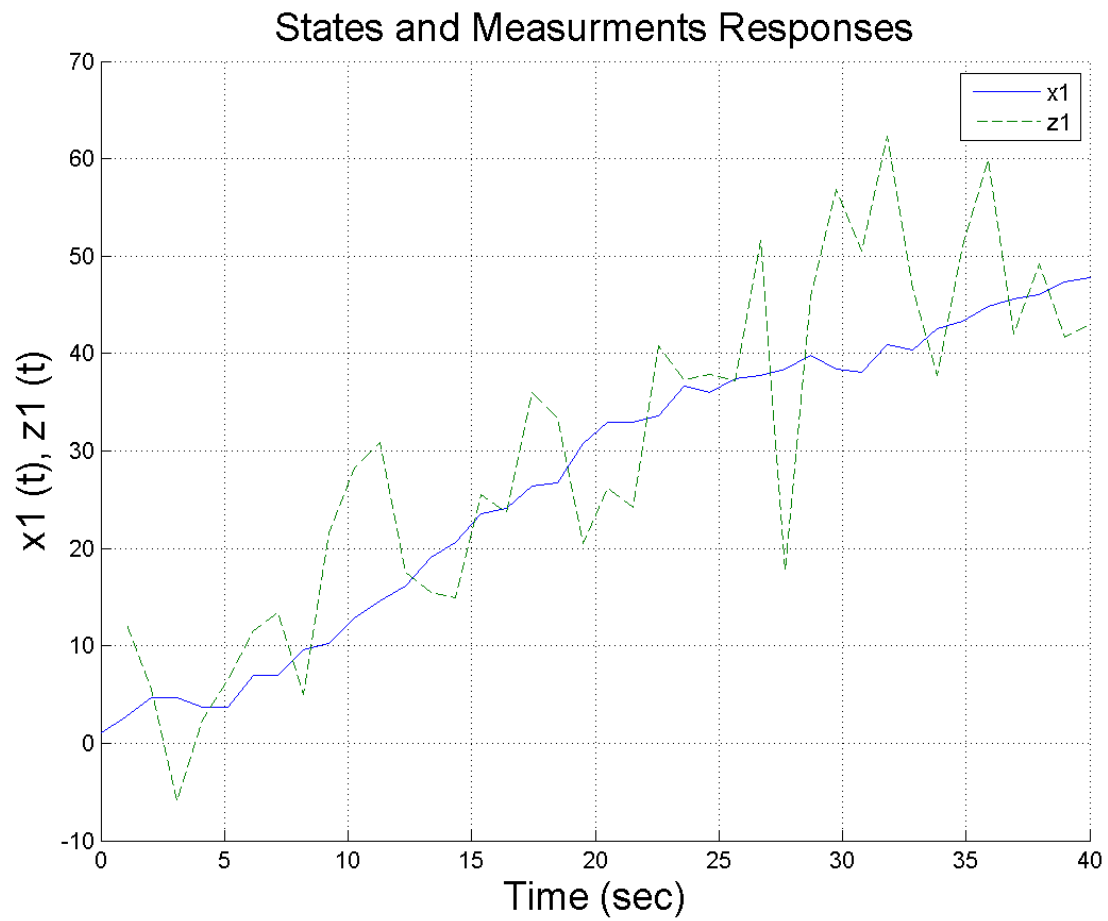


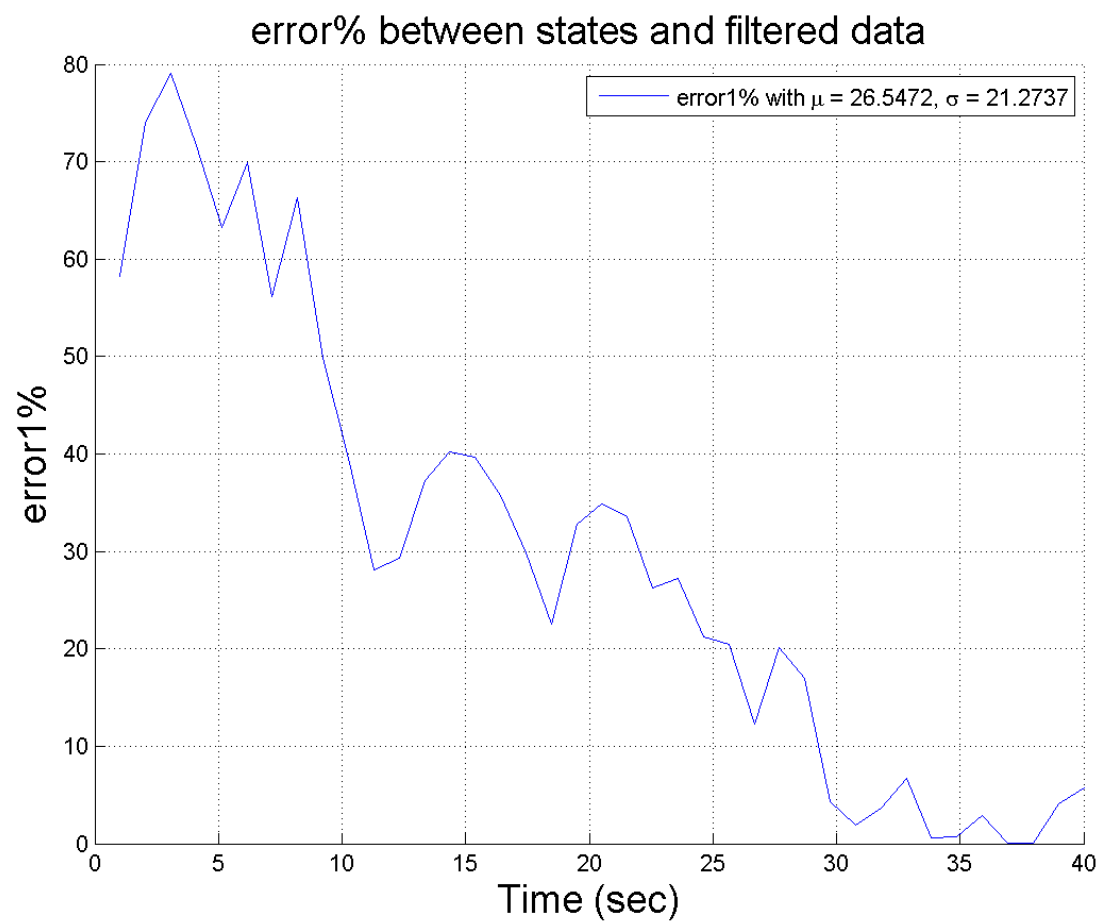
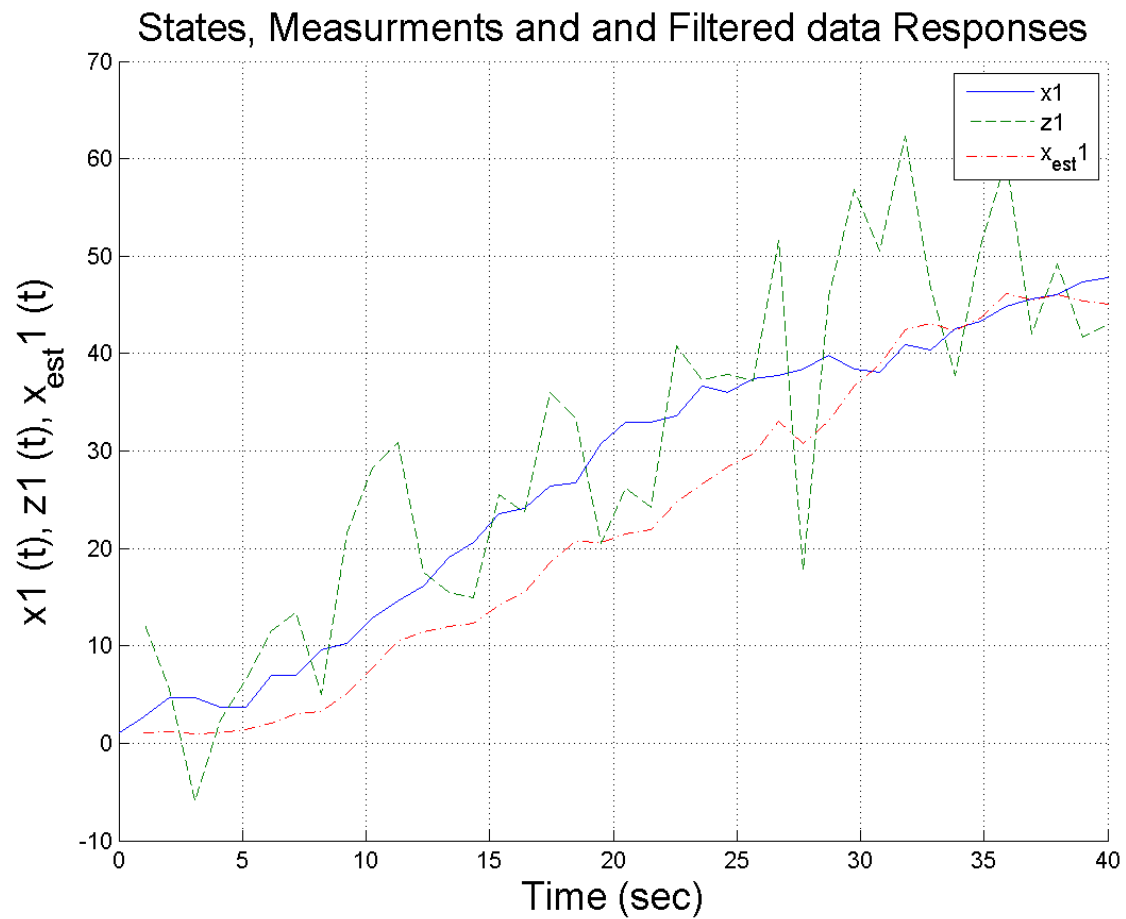


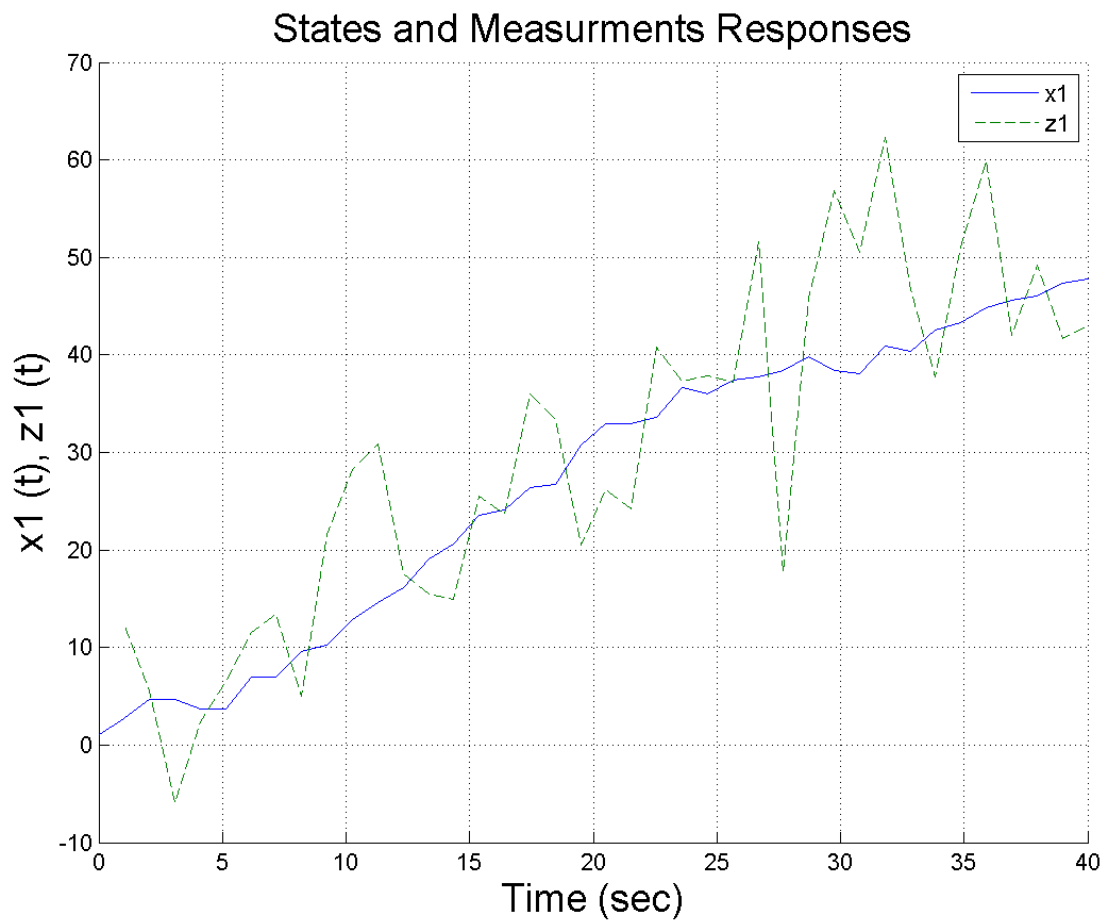
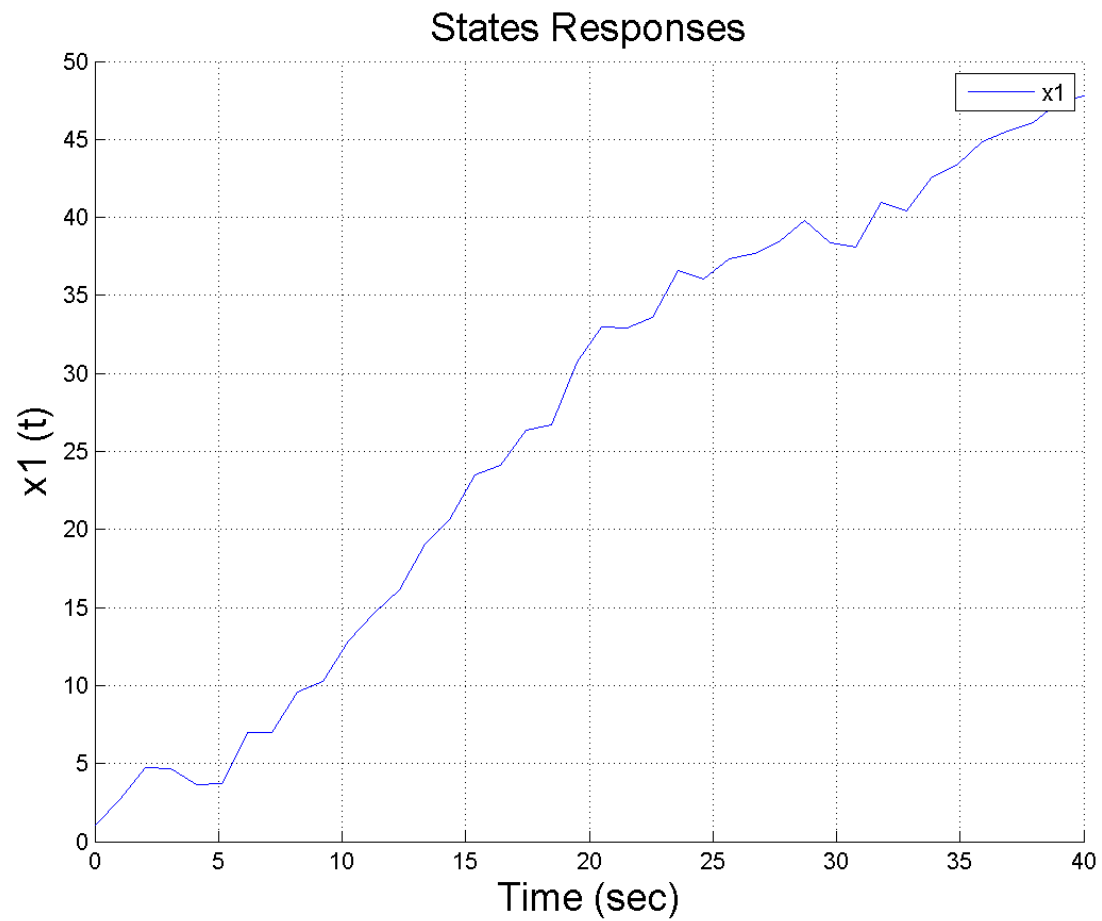


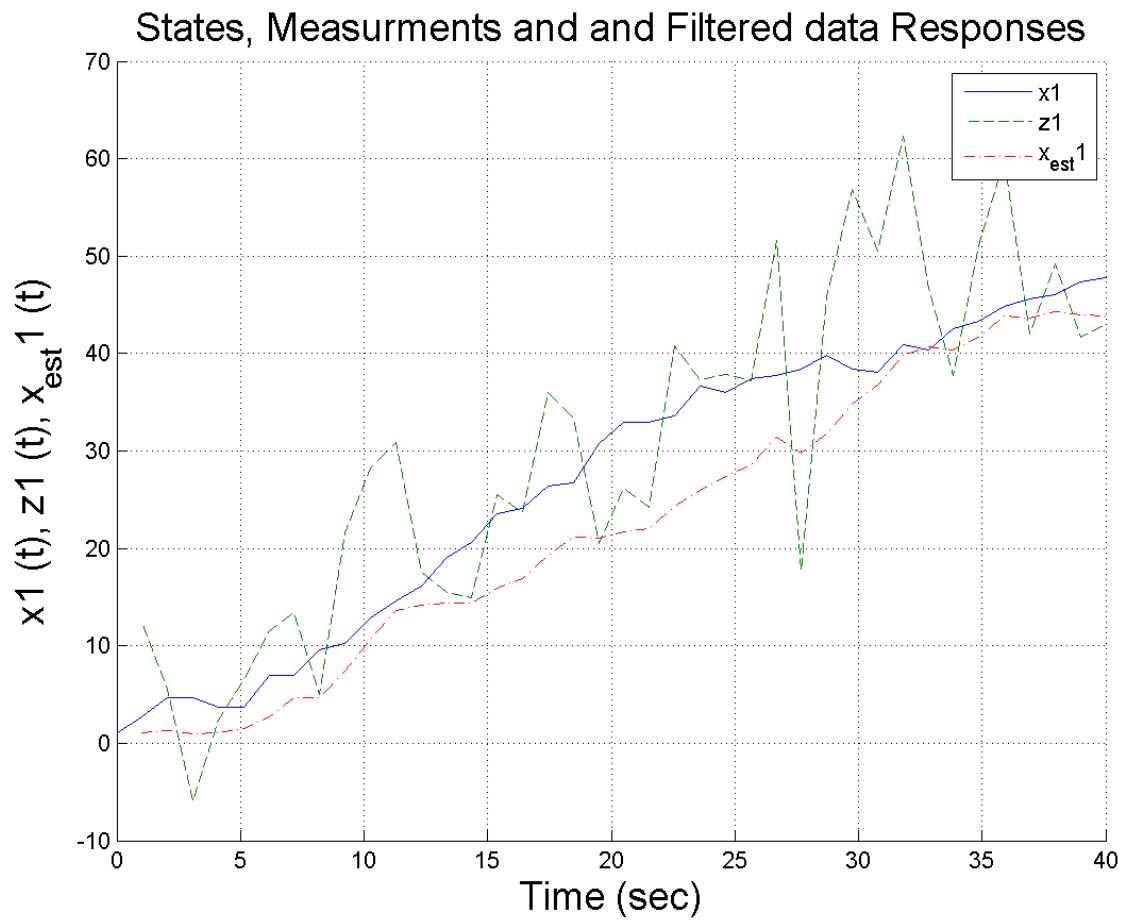
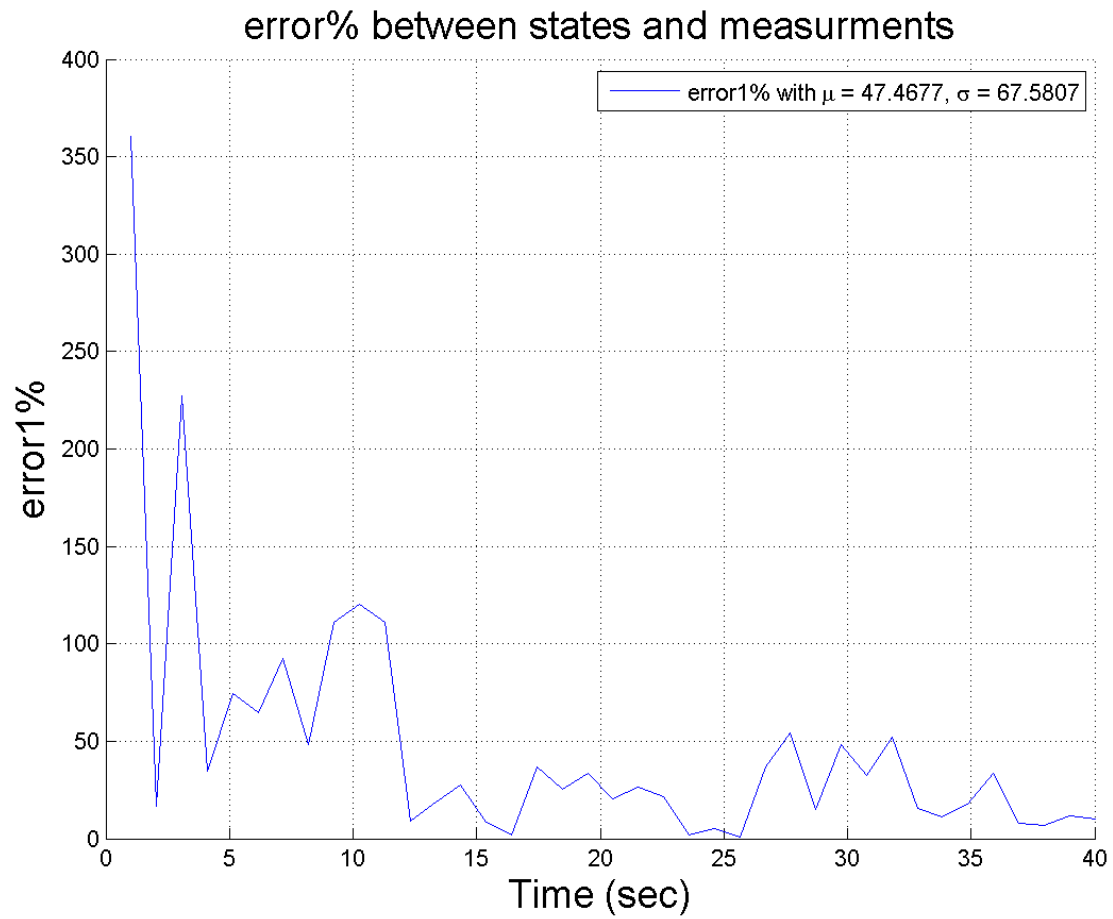
Discrete Kalman Filter with Forgetting Factor λ :

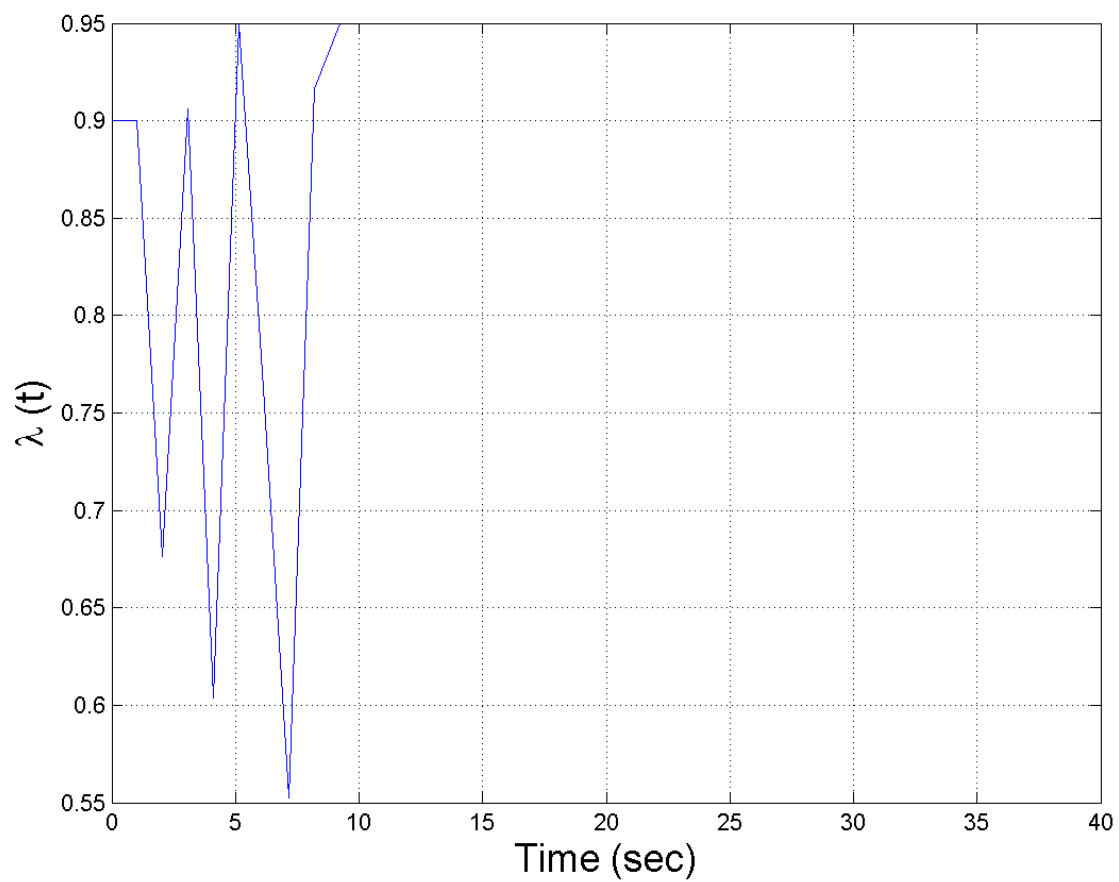






Discrete Kalman Filter with Varying Forgetting Factor λ :





Comments:

From results we see that the $error\%$ have the data,

	DKF	DKF with λ	DKF with varying λ
μ	38.3429	26.5472	22.7235
σ	20.224	21.2737	17.5789

It's seems that DKF with varying λ has the min. μ and σ