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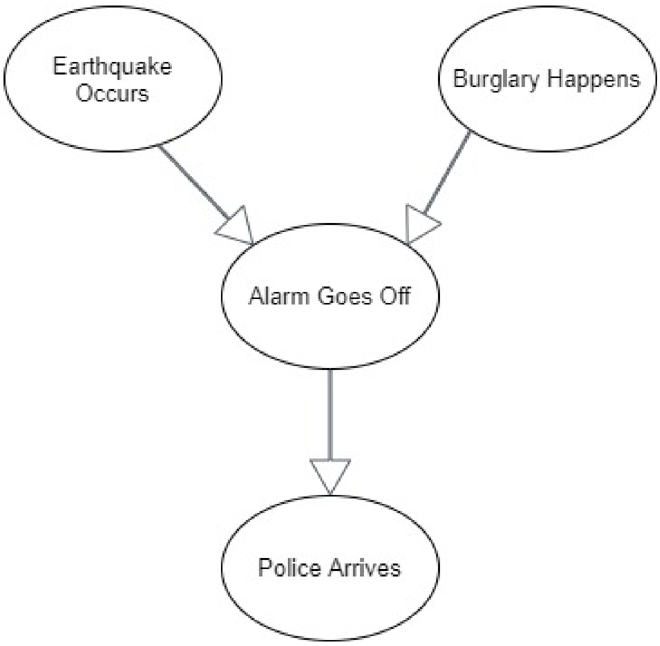
1

(a) No, robot actions do not always increase uncertainty. Consider a case when we are not certain of the position of the robot in a room. Now if the robot takes a step forward and hits a wall or a known object, we most probably know exactly know where the robot is inside the room. Thus uncertainty can decrease with robot actions.

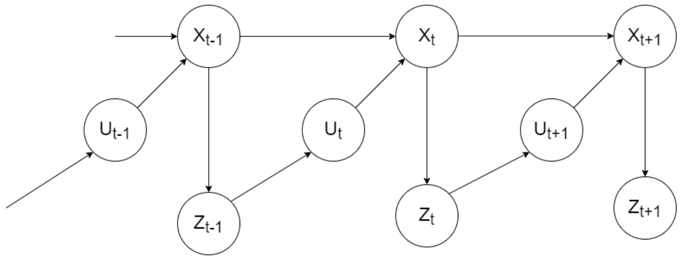
(b) If at any point, the probability of state assignment becomes 1, this creates a problem for us. This is because it eliminates the uncertainty completely. If the state assignment is wrong this means there is no room for uncertainty, i.e. there is no way to correct the state assignment and the chance of assignment being correct is null. It also affects all further state assignments.
One way to avoid this is to artificially introduce noise into the system. Adding some noise of normal distribution reduces the probability and increases uncertainty.

(c) Bayesian Network:



$P(E)$: Probability of Earthquake Occurring
$P(B)$: Probability of Burglary Happening
$P(A \mid E, B)$: Probability of Alarm Going off when Earthquake and Burglary Occur
$P(P \mid A)$: Probability of Police Arriving when Alarm goes off

(d) In recursive state estimation, if the controls were dependent on the observations, we would have a Bayesian Network as follows:



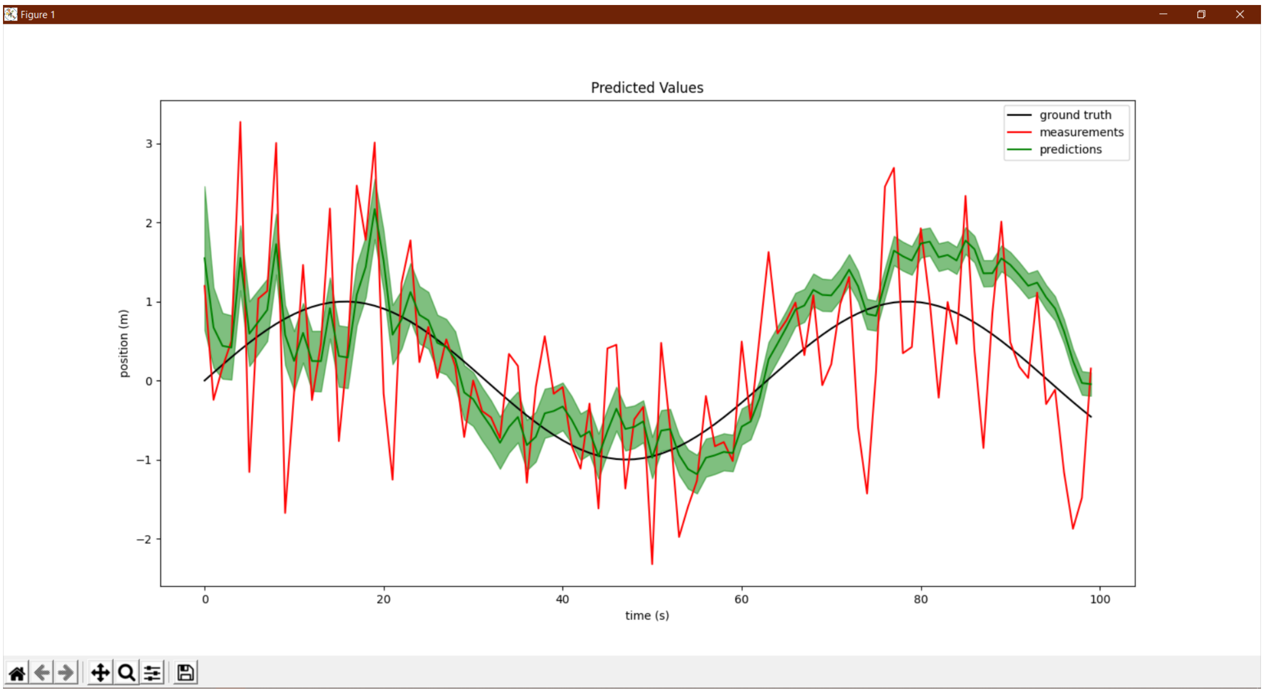
Action/Control U_t depends on observation Z_{t-1}. U_t combined with state X_{t-1} will produce state X_t which in turn will create observation Z_t and so on.

(e) Extended Kalman Filters work on non-linear functions by using First-Order Taylor expansion to linearize and approximate state transition and measurements. This means that if the functions are non-linear and have multiple hypothesis, the linearization will be a poor approximation.

In multiple hypothesis scenarios, the overall distribution will be a mixture of multiple Gaussian distributions. If we apply linearization over these multiple distributions, the resultant approximation will make no sense and will not represent accurate state estimation and transition. Hence EKFs fail to handle such cases.

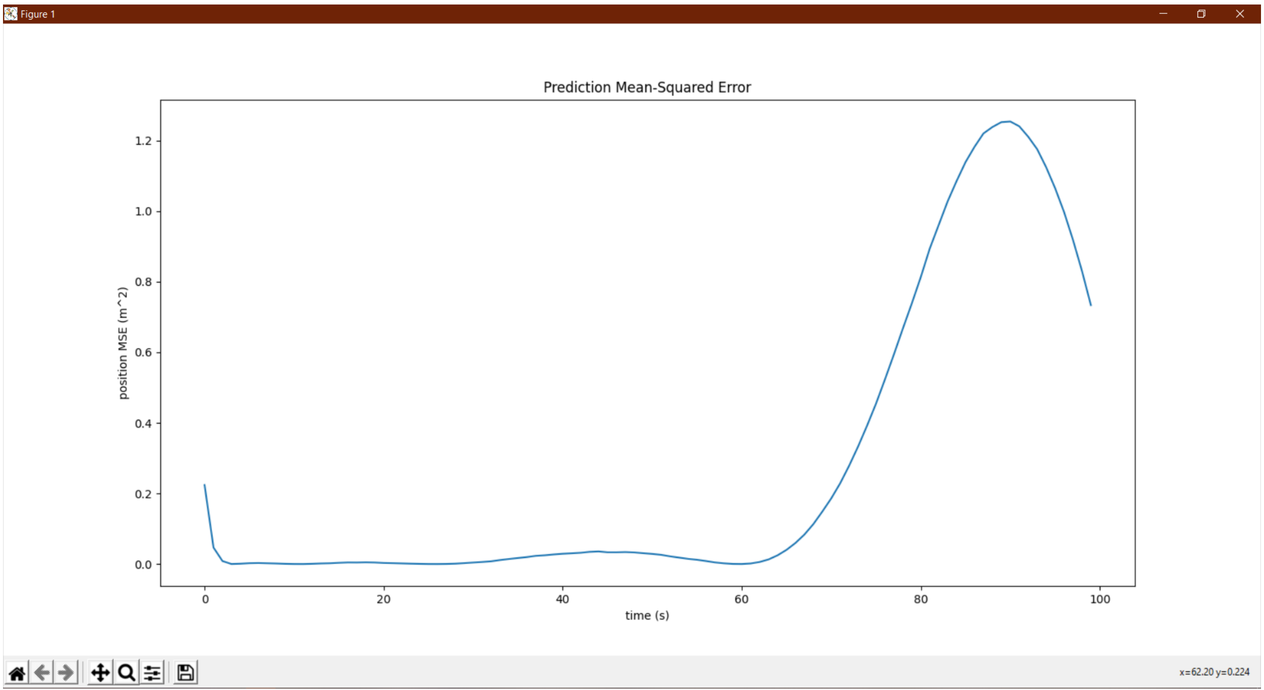
2

(a) Predicted values compared to ground truth values:



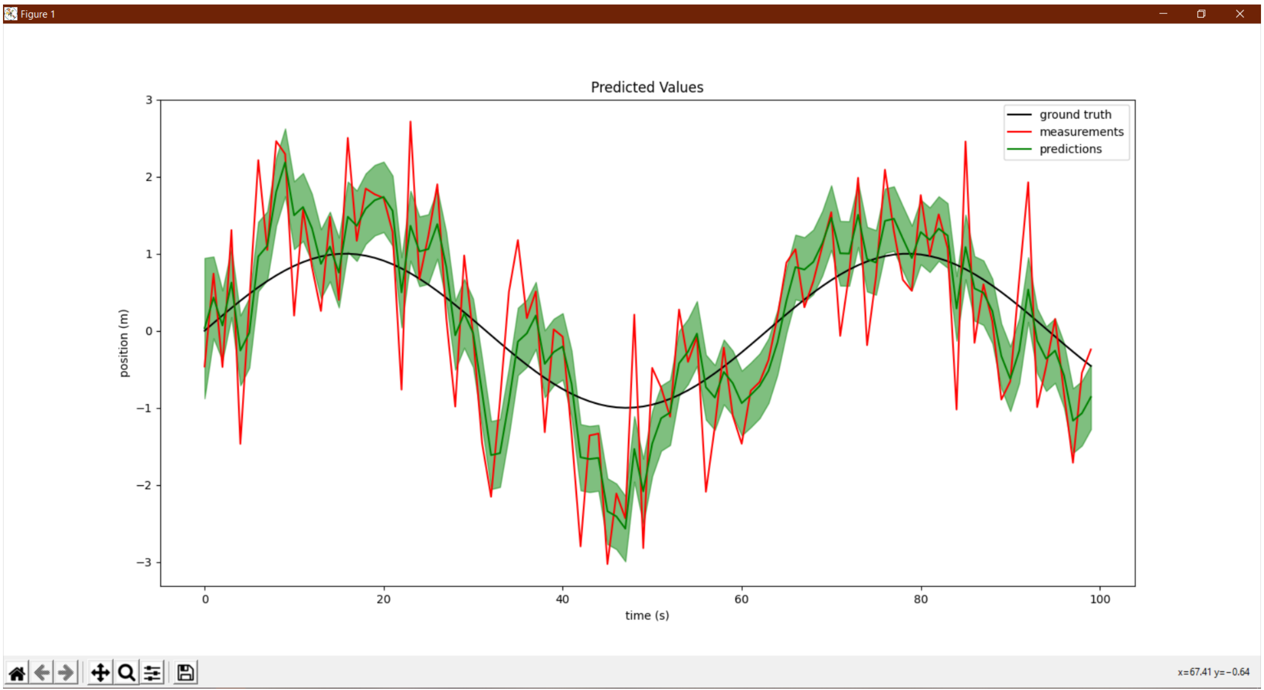
problem2a_kf_estimation.jpg

Mean Square Error computed over 10000 Trials:



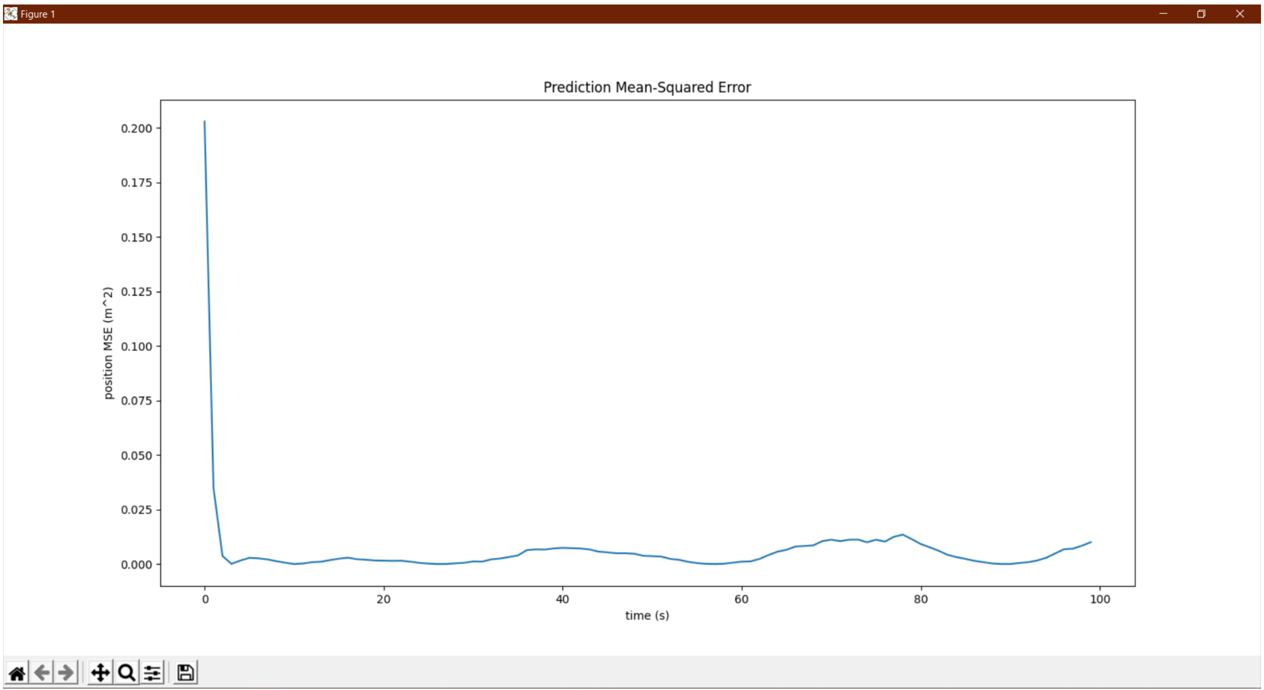
problem2a_kf_mse.jpg

(b) Predicted values compared to ground truth values with added fictitious noise:



problem2b_kf_estimation.jpg

Mean Square Error computed over 10000 Trials:



problem2b_kf_mse.jpg

3

(a) As per hint, we need to append the unknown parameter α to x to make the state vector.

$$X_t = \begin{bmatrix} x_t \\ \alpha_t \end{bmatrix}$$

Dynamic model for state t:

$$\begin{aligned} X_t &= \begin{bmatrix} x_t \\ \alpha_t \end{bmatrix} \\ &= \begin{bmatrix} \alpha_{t-1} * x_{t-1} \\ \alpha_{t-1} \end{bmatrix} \end{aligned}$$

Values for Extended Kalman Filter:

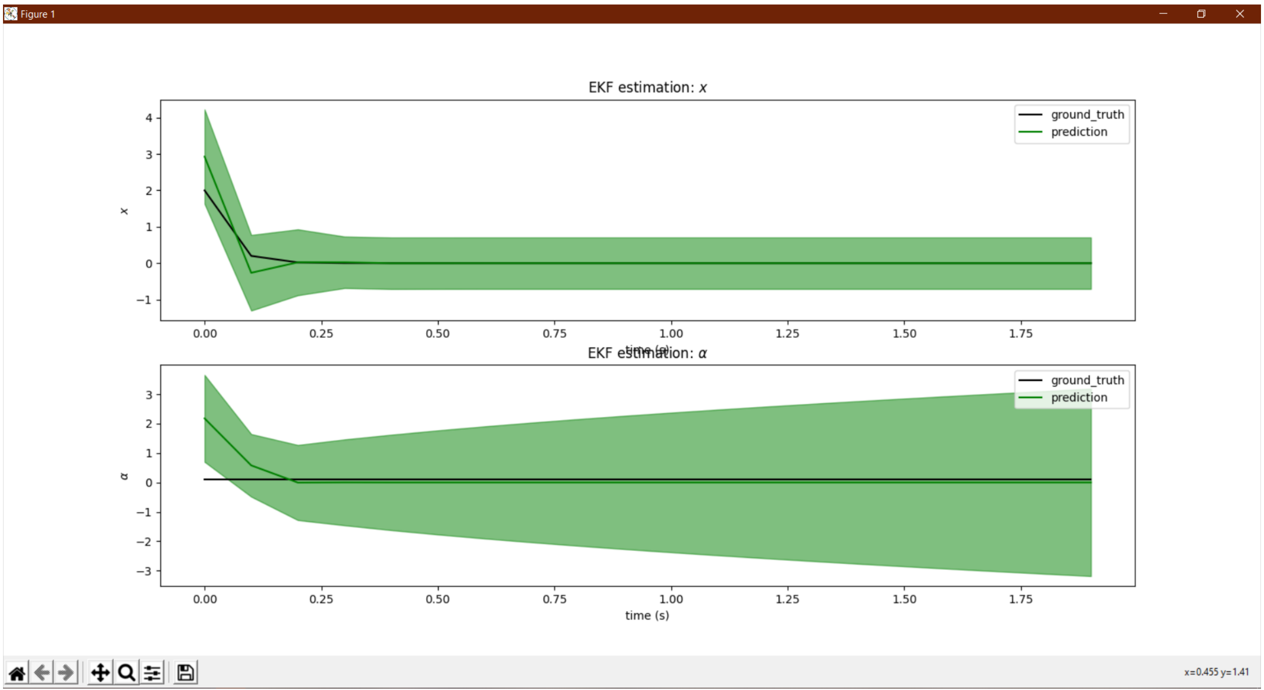
$$g = \begin{bmatrix} \alpha_t * x_t \\ \alpha_t \end{bmatrix}$$

$$g\_jac = G = \begin{bmatrix} \alpha_t & x_t \\ 0 & 1 \end{bmatrix}$$

$$h = \sqrt{x_t^2 + 1}$$

$$h\_jac = H = \begin{bmatrix} \frac{x_t}{\sqrt{x_t^2+1}} & 0 \end{bmatrix}$$

(b) Estimation of x and α



problem3_ekf_estimation.jpg