

Moving Horizon Estimation

Nirav Raiyani

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1 Model

The original discrete time state space model is of the form:

$$x_{k+1} = f(x(k), u(k)) + w(k) \quad (1)$$

$$y(k) = Cx(k) + v(k) \quad (2)$$

where,

$w(k)$ = Process noise with co-variance \mathbf{Q} .

$v(k)$ = Measurement noise with co-variance \mathbf{R} .

2 Cost Function

The full information problem becomes computationally intensive with time, and hence, in MHE, truncated sequence $(x_{k=k=T-N}^{k=T})$ of finite length N is evaluated at every step. The cost function is as follows,

$$J = \sum_{k=T-N}^{T-1} [(y_k - Cx_k)_{R-1}^2 + (x_{k+1} - f(x_k, u_k))_{Q-1}^2] + \Gamma_{T-N} \quad (3)$$

Where, Γ_{T-N} is an approximate of the arrival cost obtained by first-order Taylor series approximation (similar to EKF).

Arrival Cost (Γ_{T-N}):

$$\Gamma_k = (x_k - \hat{x}_k)_{P_k^{-1}}^2 \quad (4)$$

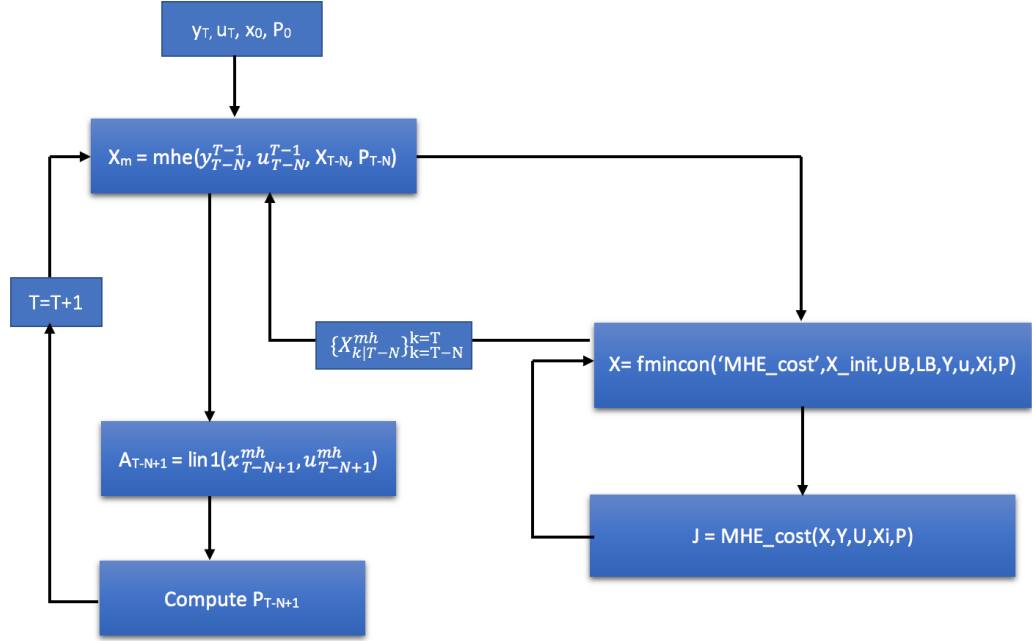
Where, matrix P is obtained by solving the Riccati equation

$$P_{k+1} = A_k P_k A_k' - A_k P_k C' (C P_k C' + R)^{-1} C P_k A_k' + Q \quad (5)$$

Where,

$$A_k = \frac{\partial f(x_k, u_k)}{\partial x} \Big|_{(x_k^{mh}, u_k)} \quad (6)$$

3 Matlab Flow



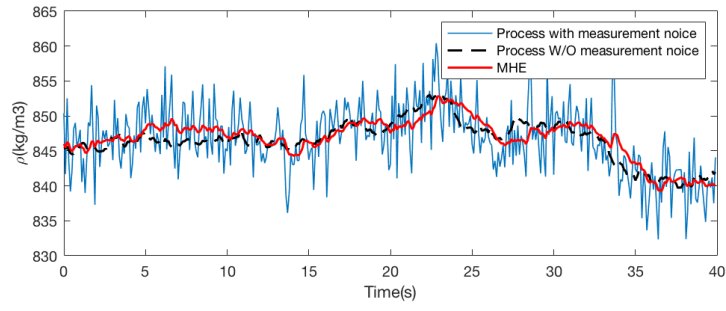
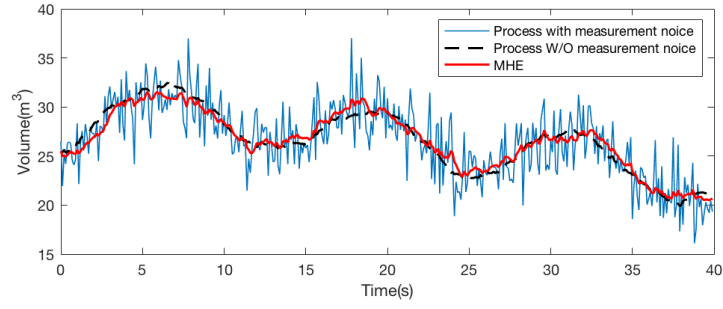
The figure describes the MATLAB flow for MHE.

- step 1: The function **mhe** takes Output measurements $([y_k]_{k=T-N}^{T-1})$, Input $([u_k]_{k=T-N}^{T-1})$, Initial guess of states (x_0) and P_0 as an input and gives states estimate $([x_k]_{k=T-N}^T)$ as an output.
- step 2: **mhe** uses MATLAB function **fmincon** to perform constrained non-linear optimization for state evaluation. UB and LB incorporates the lower and upper bounds imposed on the evaluated stats.
- step 3: The function fmincon uses **MHE cost** to evaluate the cost for given states as per equation (3).
- step 4: Once the states are evaluated, function **lin1** linearizes the system equation around x_{T-N+1}^{mh} and returns value of A as per equation (6).
- step 5: P_{T-N+1} is calculated using equation(5) and A obtained in previous step.
- step 6: $T = T+1$ and go back to step 1.

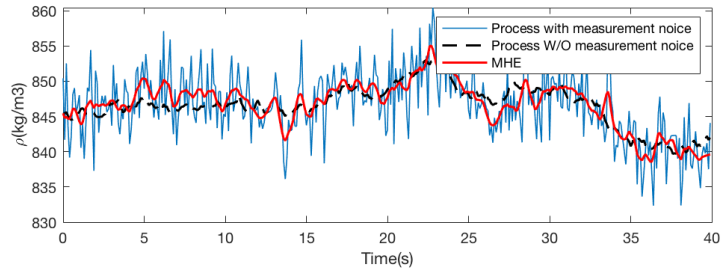
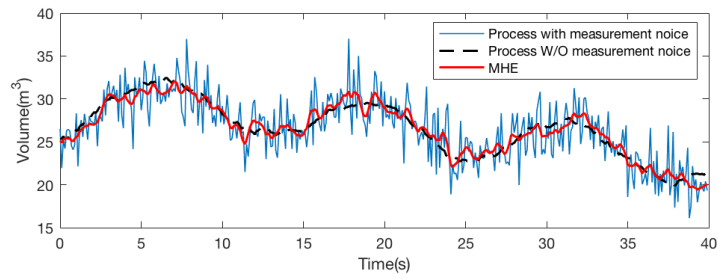
4 Results

The results with different window length are shown below.

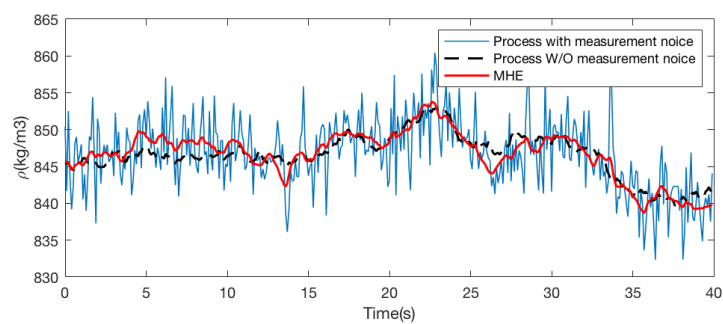
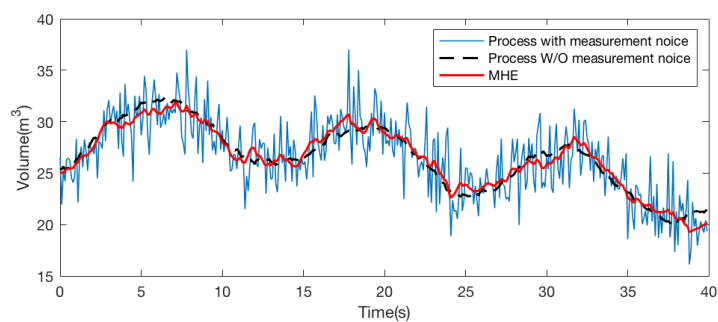
- $N = 1$



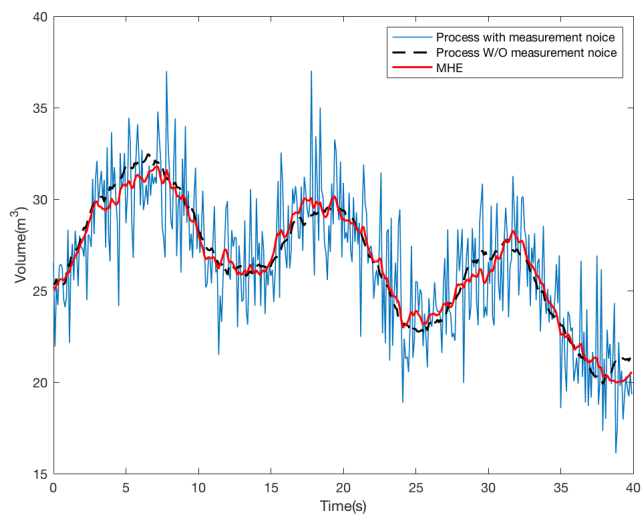
- $N = 5$

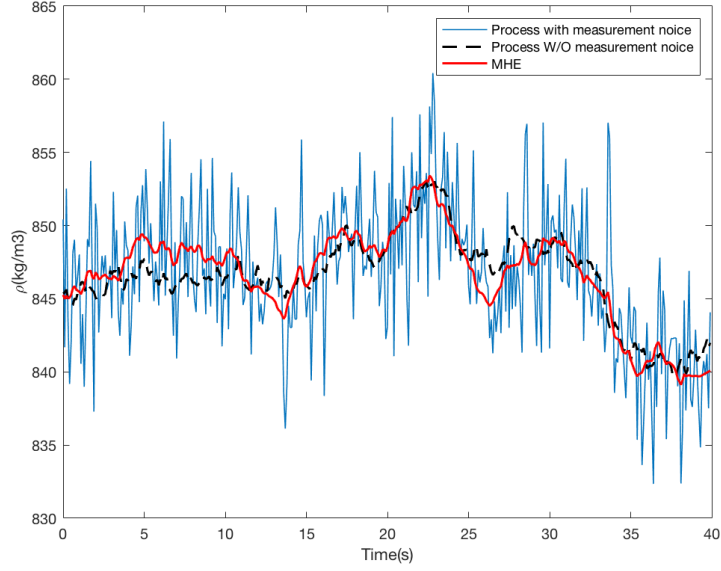


- $N = 10$



- $N = 15$





As it can be seen that increasing the window length is not bringing any significant improvement in the results.

The above results are obtained using following parameters,

- Sampling time, $T_s = 0.1s$.

- Window Size, $N = 15$.

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$$C = \begin{bmatrix} 1.268 & 0 \\ 0 & 1 \end{bmatrix}$$

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$$P_0 = \begin{bmatrix} 0.5 & 0 \\ 0 & 1.5 \end{bmatrix}$$

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$$Q = \begin{bmatrix} 0.05 & 0 \\ 0 & 0.1 \end{bmatrix}$$

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$$R = \begin{bmatrix} 5 & 0 \\ 0 & 10 \end{bmatrix}$$

- Process Model:

$$V_{k+1} = V_k + T_s(-0.015\sqrt{V_k} + F_{1k} + F_{2k}) \quad (7)$$

$$\rho_{k+1} = \rho_k + \frac{T_s}{V}[(823 - \rho)F_{1k} + (890 - \rho)F_{2k}] \quad (8)$$

5 References

- [1] C. V. Rao, J. B. Rawlings and D. Q. Mayne, "Constrained state estimation for nonlinear discrete-time systems: stability and moving horizon approximations," in IEEE Transactions on Automatic Control, vol. 48, no. 2, pp. 246-258, Feb. 2003. doi:10.1109/TAC.2002.808470
- [2] Yi Zhang, On the Fundamentals of Moving Horizon Estimation.
- [3] H. Sandberg, Moving Horizon Estimation. Lecture Notes, California Institute of Technology. Available at <http://www.cds.caltech.edu/~murray/wiki/images/b/b3/Stateestim.pdf>.