Comparing EKF and UKF in the State Estimation of Hydraulically Actuated Machines

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EXTENDED ABSTRACT

1 Introduction

Machine states and parameters can be predicted using information-fusing techniques, where simulation models are combined with sensor measurements. Among various methods in the literature, Kalman filters have been actively investigated in the framework of multibody simulation [1, 2, 3], especially, the extended Kalman filter (EKF) and the unscented Kalman filter (UKF). The UKF hands the nonlinearity of the model as it is, where the EKF locally linearizes the model resulting in performance degradation [4]. This performance degradation can be overcome by using an improved version of the EKF [5]. Nevertheless, the application of the improved EKF in the state estimation of hydraulic machines is an open-field of research.

The objective of this study is to introduce state estimators using an improved EKF and compare it with the UKF in the framework of hydraulically actuated machines. To this end, a forestry crane is demonstrated where the mechanics are modeled using the coordinate partitioning method, and the hydraulics is modeled using the lumped fluid method. This study utilizes dummy/artificial measurements using a reference model representing the real system. The imperfect/simulation model considers modeling errors in the force model. The accuracy and efficiency of the state estimators are compared in various sensor configurations.

2 Modeling of Hydraulic Machines

It is well-established in the literature that the coupled dynamics of a hydraulic machine can be written as [2, 3]

$$\left.\begin{aligned} \mathbf{R}_z^{\mathrm{T}}\bar{\mathbf{M}}^{\Sigma}\mathbf{R}_z\ddot{\mathbf{z}}^{\mathrm{i}} &= \mathbf{R}_z^{\mathrm{T}}\left(\bar{\mathbf{Q}}^{\Sigma} - \bar{\mathbf{M}}^{\Sigma}\dot{\mathbf{R}}_{\mathbf{z}}\dot{\mathbf{z}}^{\mathrm{i}}\right) \\ \dot{\mathbf{p}} &= \mathbf{u}_0 \end{aligned}\right\}, \tag{1}$$

where $\bar{\mathbf{M}}^{\Sigma}$ and $\bar{\mathbf{Q}}^{\Sigma}$ are the respective accumulated mass matrix and external force vector, $\mathbf{z}^{\mathrm{i}}$, $\dot{\mathbf{z}}^{\mathrm{i}}$, and $\ddot{\mathbf{z}}^{\mathrm{i}}$ are the vectors of independent relative joint positions, velocities, and accelerations, $\mathbf{p}$ and $\dot{\mathbf{p}}$ are the respective vectors of pressures and pressure build-ups, $\mathbf{u}_0$ is the function of pressure variation equations, and $\mathbf{R}_z$ is the velocity transformation matrix that can be written as

$$\mathbf{R}_z = \begin{bmatrix} -\left(\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{d}}\right)^{-1}\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{i}} \\ \mathbf{I} \end{bmatrix}, \tag{2}$$

where $\mathbf{\Phi}_{\mathbf{z}}$ is the Jacobian matrix of the loop-closure constraints vector $\mathbf{\Phi}$, $\mathbf{I}$ is an identity matrix, and $\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{i}}$ and $\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{d}}$ are the independent and dependent columns of the Jacobian matrix, respectively. To ensure that the inverse of $\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{d}}$ exist, redundant constraints or singular configurations are neglected.

3 Design of State Estimators

In the design of state estimator, the state vector is considered as

$$\mathbf{x} = \left[(\mathbf{z}^{\mathrm{i}})^{\mathrm{T}}, \quad (\dot{\mathbf{z}}^{\mathrm{i}})^{\mathrm{T}}, \quad \mathbf{p}^{\mathrm{T}}\right]^{\mathrm{T}}. \tag{3}$$

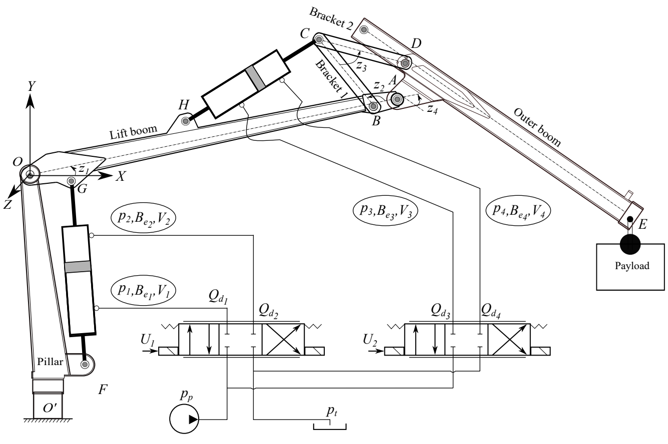
At prediction stage, EKF and UKF are initiated by an initial covariance matrix $\mathbf{P}_{k-1}^{+}$ and an independent state vector $\hat{\mathbf{x}}_{k-1}^{+}$ provided by Eq. (1). In case of UKF [4], a set of $2L+1$ sigma points χ_k is generated in which L represents the length of $\hat{\mathbf{x}}_{k-1}^{-}$. The mean independent state vector $\hat{\mathbf{x}}_k^{-}$ and the covariance matrix $\mathbf{P}_{\mathbf{k}}^{-}$ are calculated using the weights and a white Gaussian process noise $\mathbf{w}$, as mentioned in [4]. Further, using sensor measurements $\mathbf{h}_k$ and a white Gaussian measurement noise $\mathbf{v}$, the independent state vector and the associated covariance matrix are corrected for the next time step as,

$$\begin{cases} \mathbf{K_k} = \mathbf{P}_{x_k y_k}\mathbf{P}_{yk}^{-1} \\ \hat{\mathbf{x}}_k^{+} = \hat{\mathbf{x}}_k^{-} + \mathbf{K_k}(\mathbf{h_k} - \mathbf{y}_{\mathbf{k}}'^{-}) \\ \mathbf{P}_{\mathbf{k}}^{+} = \mathbf{P}_{\mathbf{k}}^{-} - \mathbf{K_k}\mathbf{P_{yk}}\mathbf{K}_{\mathbf{k}}^{\mathbf{T}} \end{cases}, \tag{4}$$

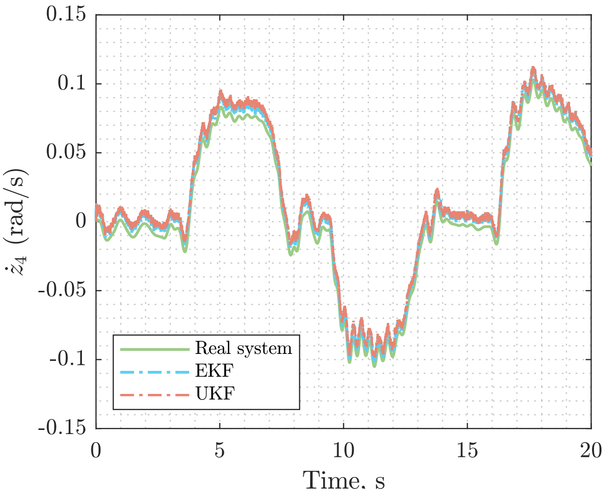
where $\mathbf{K_k}$ is the Kalman gain, $\mathbf{P}_{x_k y_k}$ and $\mathbf{P}_{yk}$ are the covariances in UKF [4] and $\mathbf{y}_{\mathbf{k}}'^{-}$ is the approximated weighted mean. In case of EKF, mean independent state vector $\hat{\mathbf{x}}_k^{-}$ and the covariance matrix $\mathbf{P}_{\mathbf{k}}^{-}$ are calculated using the Jacobian of dynamic system $\mathcal{F}_{\mathbf{x}}$ and the Jacobian of sensor measurements $\mathbf{h}_{\mathbf{x}}$. This study uses the complex variables to approximate $\mathcal{F}_{\mathbf{x}}$ of the dynamic equations mentioned in Eq. (1).

4 Results and Conclusion

UKF and EKF are implemented on the hydraulically driven system as shown in Figure 1a. Dummy sensors measurements of lift boom and outer boom angles z_1 and outer boom z_4, the pressures on the piston side of lift cylinder p_1 and outer cylinder p_3 are taken from the real system. The real system is representing another simulation model having absolute parameters. However, in the estimation model used with EKF and UKF, the simulation modeling errors are introduced in the force model. The sensor measurements were used by the state observers to estimate the state vector $\mathbf{x} = \begin{bmatrix} z_1 & z_4 & \dot{z}_1 & \dot{z}_4 & p_1 & p_2 & p_3 & p_4 \end{bmatrix}^{\mathrm{T}}$. Where the p_2 and p_4 accordingly represent the pressure on the piston-rod side of the lift and outer cylinders. The control signal vector $\mathbf{U}$ was kept the same in the measurement and state estimation process. The implementation of EKF and UKF algorithms was carried out in a MATLAB environment.



(a) Schematic diagram of forestry crane and hydraulic circuit.



(b) Angular velocity of outer boom comparison

Figure 1: Studied system and comparison result

The observers were evaluated during the estimation of the state vector $\mathbf{x}$ in a 20-second working cycle. Due to limited space, only the estimation results of $\dot{z}_4$ are shown in Figure 1b. The estimations of $\dot{z}_4$ from the estimators are close to each other, and they have small differences with respect to the real system. The differences indicate that there are errors in the estimation model. Then, the percent normalized root means square error (PN-RMSE) of the state vector was calculated to describe the estimation accuracy of UKF and EKF. The PN-RMSE of the UKF estimation is $\begin{bmatrix} 0.66\% & 0.31\% & \mathbf{2.34}\% & \mathbf{2.80}\% & 0.22\% & \mathbf{4.10}\% & 0.21\% & \mathbf{2.84}\% \end{bmatrix}^{\mathrm{T}}$. And for EKF is $\begin{bmatrix} 0.66\% & 0.31\% & \mathbf{2.36}\% & \mathbf{2.33}\% & 0.22\% & \mathbf{4.10}\% & 0.21\% & \mathbf{2.84}\% \end{bmatrix}^{\mathrm{T}}$. Where bold indicates the results without sensor measurements. The PN-RMSE of measured state variables z_1, z_4, p_1 and p_3 are below 1%. And the values for non-measured state variables are below 5%. Considering the complexity and non-linearity of the forestry crane, the result demonstrates that both the designed UKF and EKF can provide accurate estimations with low PN-RMSE value using the set of dummy measurements. It can be concluded that, through limited instrumentation set on the hydraulically driven machines, both EKF and UKF can produce estimations of non-measured states with reasonable accuracy.

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