Indirect Kalman Filter-based State Estimator for a Hydraulic Crane

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EXTENDED ABSTRACT

1 Introduction

Computer simulation of hydraulic machinery can be performed using a multibody dynamics approach. In this approach, the equations of motion are coupled with hydraulic actuators. The simulation models of hydraulic machinery are never accurate and they deviate from reality over a period of time because of modeling error accumulation. Nevertheless, the simulation models can be made to follow reality by using an information fusing technique such as a state estimator [1]. This approach can be applied in monitoring and controlling machine operations by estimating the machine states instead of measuring it.

The objective of this study is to introduce an indirect Kalman filter-based state estimator for a hydraulic crane. To this end, the error-state extended Kalman filter [2] is utilized in this study. The mechanics of the hydraulic crane is modeled using the index-3 augmented Lagrangian-based semi-recursive multibody method and the hydraulics is modeled using the classical lumped fluid method. In this study, dummy measurements are used by adding white Gaussian noise to the ground truth provided by a reference model. The state estimator considers error in the force and pressure models. The state estimator accuracy is investigated in various sensor combinations at different sampling rates of sensors.

2 State estimator based on an indirect Kalman filter

In hydraulic machinery modeling, the mechanics and hydraulics can be coupled using a monolithic approach. It is well-established in the literature that the equations of motion of the coupled mechanics and hydraulics model can be written as [3]

$$\left.\begin{aligned} \bar{\mathbf{M}}^{\Sigma}\ddot{\mathbf{z}}+\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{T}}\alpha\mathbf{\Phi}+\mathbf{\Phi}_{\mathbf{z}}^{\mathrm{T}}\lambda &= \bar{\mathbf{Q}}^{\Sigma}\left(\mathbf{z},\dot{\mathbf{z}},\mathbf{p}\right) \\ \lambda^{(h+1)} &= \lambda^{(h)}+\alpha\mathbf{\Phi}^{(h+1)} \\ \dot{\mathbf{p}} &= \mathbf{u}_0\left(\mathbf{z},\dot{\mathbf{z}},\mathbf{p}\right) \end{aligned}\right\}, \tag{1}$$

where $\bar{\mathbf{M}}^{\Sigma}$ and $\bar{\mathbf{Q}}^{\Sigma}$ are the accumulated mass matrix and external force vector, respectively, $\mathbf{z}$, $\dot{\mathbf{z}}$, $\ddot{\mathbf{z}}$ are the respective vectors of relative joint positions, velocities, and accelerations, $\mathbf{\Phi}$ is the loop-closure constraints vector and $\mathbf{\Phi}_{\mathbf{z}}$ is its Jacobian matrix, α is the penalty factor, λ is the vector of iterated Lagrange multipliers, h is the iteration step, $\mathbf{p}$ and $\dot{\mathbf{p}}$ are the vectors of pressures and pressure build-ups, respectively, and $\mathbf{u}_0$ is the function of pressure variation equations.

In every time-step, simulation model is executed to obtain $\mathbf{z}$, $\dot{\mathbf{z}}$, $\mathbf{p}$. The filter here considers the state vector $\mathbf{x}$ as

$$\mathbf{x}=\left[\left(\Delta\mathbf{z}^{\mathrm{i}}\right)^{\mathrm{T}},\ \left(\Delta\dot{\mathbf{z}}^{\mathrm{i}}\right)^{\mathrm{T}},\ \left(\Delta\mathbf{p}\right)^{\mathrm{T}}\right]^{\mathrm{T}}, \tag{2}$$

where $\Delta\mathbf{z}^{\mathrm{i}}$ and $\Delta\dot{\mathbf{z}}^{\mathrm{i}}$ are the *error* in positions and velocities of the mechanism degrees of freedom, respectively, and $\Delta\mathbf{p}$ is the *error* in pressures. The filter performs a prediction stage that is dependent on the transition model as [2]

$$\hat{\mathbf{x}}_k^- = \mathbf{0} \qquad \text{and} \qquad \mathbf{P}_k^- = \left(\bar{\mathbf{f}}_{\mathbf{x}}\right)_{k-1}\mathbf{P}_{k-1}^+\left(\bar{\mathbf{f}}_{\mathbf{x}}\right)_{k-1}^{\mathrm{T}}+\left(\textstyle\sum^P\right)_{k-1}, \tag{3}$$

where $\hat{\mathbf{x}}^-$ and $\hat{\mathbf{x}}^+$ are the respective predicted and corrected means of the state, $\mathbf{P}^-$ and $\mathbf{P}^+$ are the associated covariance matrices, respectively, $\bar{\mathbf{f}}_{\mathbf{x}}$ is the Jacobian matrix of the state transition model $\bar{\mathbf{f}}\left(\cdot\right)$, k is a time-step, and $\sum^P$ is the covariance matrix of the plant noise. Furthermore, the filter performs a correction stage that relies on the measurements as [2]

$$\mathbf{y}_k = \mathbf{o}_k - \mathbf{h}\left(\mathbf{z}_k,\dot{\mathbf{z}}_k,\mathbf{p}_k\right) \qquad \text{and} \qquad \mathbf{S}_k = \left(\mathbf{h}_{\mathbf{x}}\right)_k\mathbf{P}_k^-\left(\mathbf{h}_{\mathbf{x}}\right)_k^{\mathrm{T}}+\left(\textstyle\sum^S\right)_k, \tag{4}$$

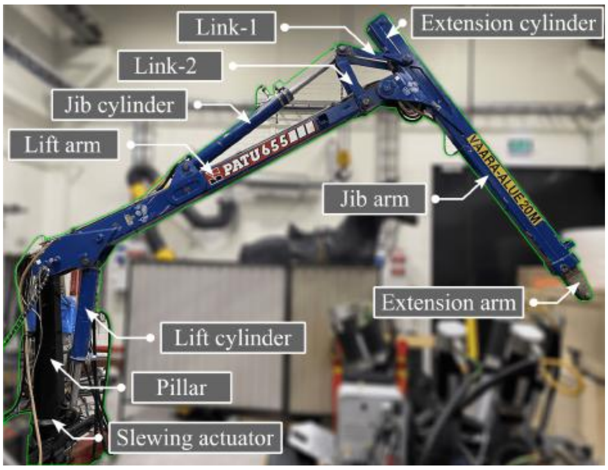
$$\mathbf{K}_k = \mathbf{P}_k^-\left(\mathbf{h}_{\mathbf{x}}\right)_k^{\mathrm{T}}\mathbf{S}_k^{-1}, \tag{5}$$

$$\hat{\mathbf{x}}_k^+ = \mathbf{0}+\mathbf{K}_k\mathbf{y}_k \qquad \text{and} \qquad \mathbf{P}_k^+ = \left[\mathbf{I}_{\left(2N_f+N_p\right)}-\mathbf{K}_k\left(\mathbf{h}_{\mathbf{x}}\right)_k\right]\mathbf{P}_k^-, \tag{6}$$

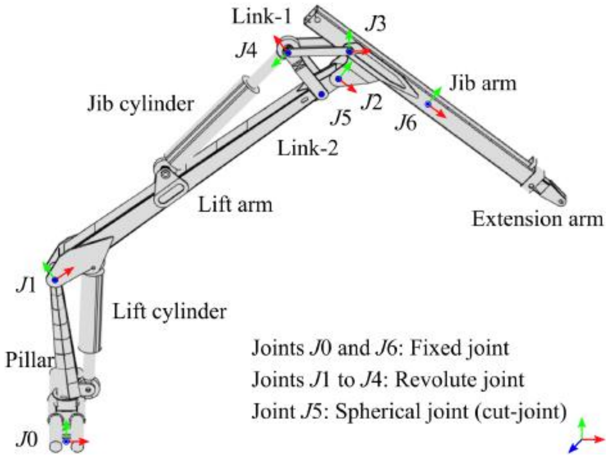
where $\mathbf{y}$ is the innovation vector and $\mathbf{S}$ is its associated covariance matrix, $\mathbf{o}$ is the measurement vector, $\mathbf{h}\left(\cdot\right)$ is the sensor model and $\mathbf{h}_{\mathbf{x}}$ is its Jacobian matrix, $\sum^S$ is the covariance matrix of the measurement noise, and $\mathbf{K}$ is the Kalman gain matrix. Post correction stage, the estimated *errors* are used to update the simulation model. Updating the mechanism degrees of freedom (independent coordinates) is straightforward, however, the dependent coordinates are updated using the constraint manifold.

3 Case example of a hydraulic crane

This study considers a case example of the hydraulic crane shown in Fig. 1. Here, a *"reference model"* presents the hydraulic crane providing the ground truth, the *"simulation model"* is an imperfect representation of the reference model, and the *"state estimator"* combines the imperfect model with the measurements from the reference model.



(a) The PATU 655 hydraulic crane at the LUT University, Finland

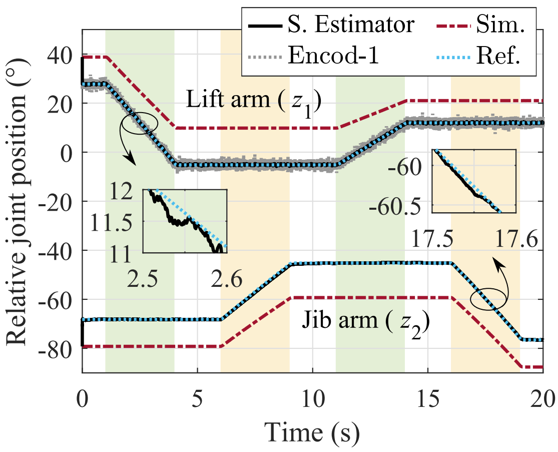


(b) State estimator of the hydraulic crane at the LUT University

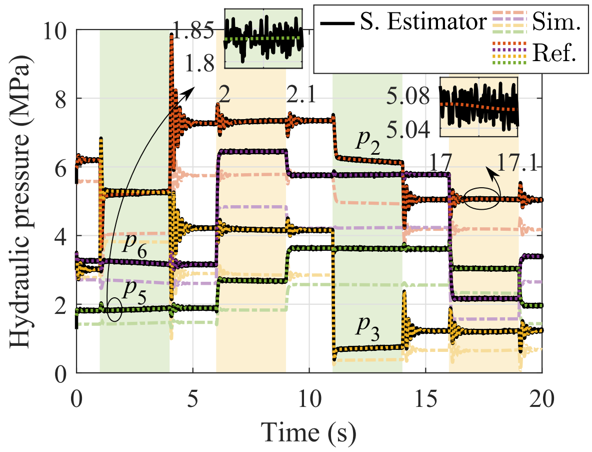
Figure 1: Case example of the hydraulic crane used in this study

4 Tests and results

Figure 2 illustrates the estimation accuracy of the estimator. It can be seen that the estimator is able to estimate the position of the jib arm without directly measuring it. Furthermore, the hydraulic pressures are estimated with sufficient accuracy.



(a) Position estimates with encoders on the lift arm and link-1



(b) Pressure estimates with pressure transducers at all control volumes

Figure 2: Accuracy estimation of the state estimator with 1000 Hz sampling rate of the sensors

5 Conclusion

This study introduced a novel state estimator for a hydraulic crane using the error-state extended Kalman filter and a multibody model. The state estimator was able to estimate the jib arm position without directly measuring it. It also provided accurate estimations at the pressure level. For future works, the proposed estimator can be tested with real sets of measurements.

References

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