Kalman Filter for Integrated Kinematics of Multibody Systems and Hydraulic Systems

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Abstract

Monitoring and control of advanced mechatronic systems requires precise data on the current state of the system. This often involves equipping the systems with appropriate sensors. However, measuring all variables is not always economically or technically viable, and their values must be computationally determined. State estimation is a method that merges prior knowledge of system behavior (the model) with observed behavior (measurements) to infer deeper system insights (virtual measurements). Within multibody systems, this prior knowledge typically includes the equations of motion of the system [1].

However, these equations can sometimes be significantly offset by factors like unknown contact forces or undetermined mass properties. In such scenarios, the kinematic Kalman filter emerges as a robust alternative [2]. This technique disregards the equations of motion as prior knowledge and instead utilizes acceleration data to drive the estimation. This work presents the key findings of the recently published work by the authors [3], where the kinematic Kalman filter approach is extended by substituting acceleration data with hydraulic pressure measurements and leveraging the established relationship between kinematics and hydraulic pressures.

The proposed estimator is based on the use of discrete extended Kalman filter and a state-space model coupling multibody kinematics with the dynamics of hydraulics as [3]:

$$\dot{\mathbf{X}} \equiv \frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix}\mathbf{z}\\ \dot{\mathbf{z}}\\ \ddot{\mathbf{z}}\\ \mathbf{p}\\ \mathbf{U}_{val}\end{bmatrix} = \begin{bmatrix}\dot{\mathbf{z}}\\ \ddot{\mathbf{z}}\\ \mathbf{0}\\ \mathbf{B}_{e,rel}\circ\left(\mathbf{T}_{p,Q}\mathbf{Q}_{val}-\mathbf{T}_{V,cyl}\dot{\mathbf{V}}_{cyl}\right)\\ \left(\mathbf{U}_{val,in}-\mathbf{U}_{val}\right)\boldsymbol{\tau}_{val}^{-1}\end{bmatrix} \equiv \boldsymbol{f}(\mathbf{z},\dot{\mathbf{z}},\ddot{\mathbf{z}},\mathbf{p},\mathbf{U}_{val};\mathbf{U}_{val,in}), \tag{1}$$

where $\mathbf{X}$ is the state vector, $\mathbf{z}$, $\dot{\mathbf{z}}$ and $\ddot{\mathbf{z}}$ are the vectors of respective cylinder positions, velocities and accelerations (considering cylinder positions as independent coordinates), $\mathbf{p}$ is a vector of pressures in the control volumes, $\mathbf{U}_{val}$ and $\mathbf{U}_{val,in}$ are vectors of spool positions and control signals, respectively, and $\boldsymbol{\tau}_{val}$ is a diagonal matrix of valve time constants. The matrix $\mathbf{T}_{p,Q}$ is a path matrix with values -1, 0 and 1 defining the connections of flows. The matrix $\mathbf{T}_{V,cyl}$ is a Boolean matrix performing the mapping between cylinder chambers and control volumes. Additionally, $\mathbf{Q}_{val}$ represent a vector of flow rates through the valves, $\mathbf{B}_{e,rel}$ is a vector of effective bulk modules divided by the corresponding control volume, and $\dot{\mathbf{V}}_{cyl}$ is a vector of time derivatives of the cylinder chamber volumes.

The estimation approach was tested by applying it to a numerical example of a simple hydraulic crane illustrated in Fig. 1. The approach was verified using synthetic measurement data. In the case example, the crane was lifting a payload, of which mass was assumed unknown. Based on position and pressure measurements and the state-space model defined in Eq. (1), the kinematic state and hydraulic pressures were estimated. The kinematic estimations with numeric data are presented in Fig. 2. In the figure, precise value refers to the one provided by the simulation before corrupting it with noise to emulate the real measurement scenario.

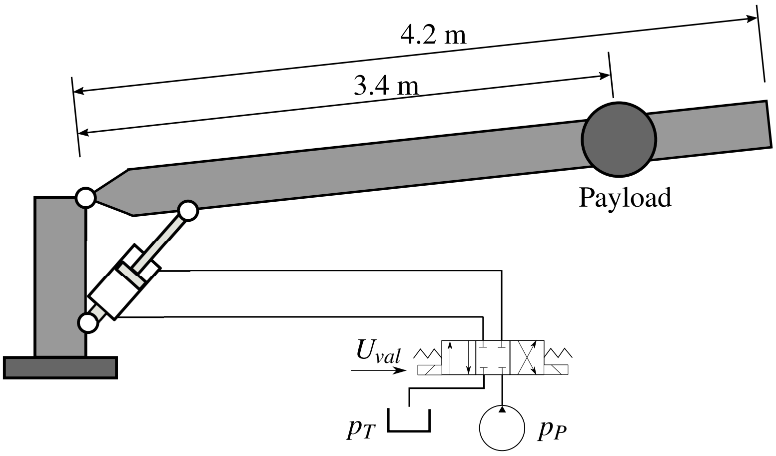
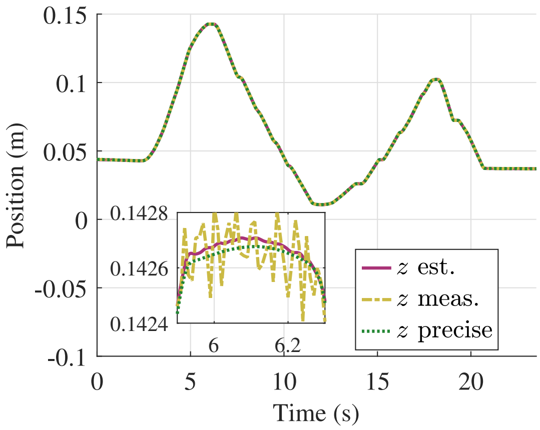
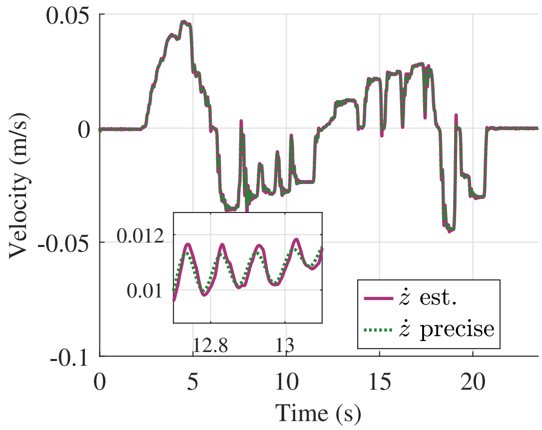


Figure 1: Crane used as a demonstrator, p_T and p_P referring to the pressure sources of hydraulic pump and reservoir, respectively



(a) Piston position estimation results



(b) Piston velocity estimation results

Figure 2: Kinematic estimation results with artificial measurement data

The proposed method facilitates precise estimation of the kinematic state of hydraulically actuated multibody systems, even when the equations of motion are not precisely known. Additionally, these kinematic estimates enable the calculation of unknown inertial parameters. In [3], this was achieved by directly solving the inverse dynamics problem. However, the method described in [4] employs a linear-regression-based identification approach, which could be coupled with the kinematic estimation approach allowing simultaneous identification of multiple inertial parameters.

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