Testing the efficiency and accuracy of multibody-based state observers

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Abstract

Multibody simulations are a standard in the industry to speed up the development of new products. Since many years ago, this tool was employed offline to predict the behavior of new concepts, or extreme situations which are difficult or expensive to attain with a prototype. After that, with the development of new multibody formulations and the increase of computational power, real-time multibody simulations became a reality, allowing people and machines to interact with the multibody models in simulators and virtual test benches. Nowadays, with the advent of low cost, low power consumption computers, a multibody simulation could be run in vehicles or robots as part of their control algorithms, providing information about immeasurable magnitudes. The problem with this approach is that, in general, a multibody model can be very accurate in the short term if the forces are accurately known, but it will diverge over the time.

For this reason, multibody models should be corrected with information from the actual mechanisms in order to be used as reliable state observers. One way to reach this aim is employing information fusion techniques to combine information about multibody models with data provided by real sensors installed on the machine. A prominent example of information fusion technique is the Kalman filter (KF) which, however, presents some problems regarding its direct application to this problem. Firstly, the KF was originally formulated for first order, linear and unconstrained models, whereas multibody models are, in general, second order, highly nonlinear, and constrained systems. Moreover, the algorithm should be efficient in order to be run in real time. Because of these reasons, this is an open field of research.

In a previous work [1], some existing methods [2, 3], and several new formulations were tested with different modeling errors and with different levels of sensor's noise. Although all the proposed formulations work quite well, in the sense that the multibody model follows the real mechanism, the statistical properties are not fully satisfactory, primarily because many of the new state observers are overconfident, i.e., the actual accuracy of filter estimates is worse than the accuracy predicted by their own uncertainty covariance matrices.

There is another concern about these filters, because an explicit integrator has to be used with the new formulations proposed in [1]. Although this is not a problem if the corrections are available at every time step, this is not always the case. This fact could jeopardize the stability of the algorithm in a real application, specially if these methods are applied to problems with impacts or high accelerations.

In this work two new methods are presented. One of them is a method in dependent coordinates. In order to fulfill the constraints, the states are projected over the constraint manifold after the corrections are applied [4]. The other method is different from the previous ones, in the sense that it is an indirect Kalman filter. This means that the states of the observer are neither the positions nor the velocities. Errors in positions and velocities are used instead. With this approach, the multibody simulation and the Kalman filter run in parallel. This way, the variations in the Kalman filter states are slow, so that the transition model could be kept simple without any stability problem, while the multibody simulation can be implemented using any formulation and integrator. From the implementation point of view, this structure is very convenient since this state observer can be easily added to an existing multibody simulation.

These new methods and the best methods presented in [1] were tested with two mechanisms, a four-bar and a five-bar mechanism, with one and two degrees of freedom respectively. The methods selected from previous works were the discrete-time EKF with independent coordinates and the discrete-time iterated EKF with dependent coordinates because of their speed, and the continuous-time EKF and the UKF because of their accuracy. In these tests, different sets of of sensors were tested (gyroscopes and encoders), considering several levels of noise and sampling rates. Moreover, various levels of modeling errors were considered in the multibody model. To provide a reference level for attainable accuracy, to which all

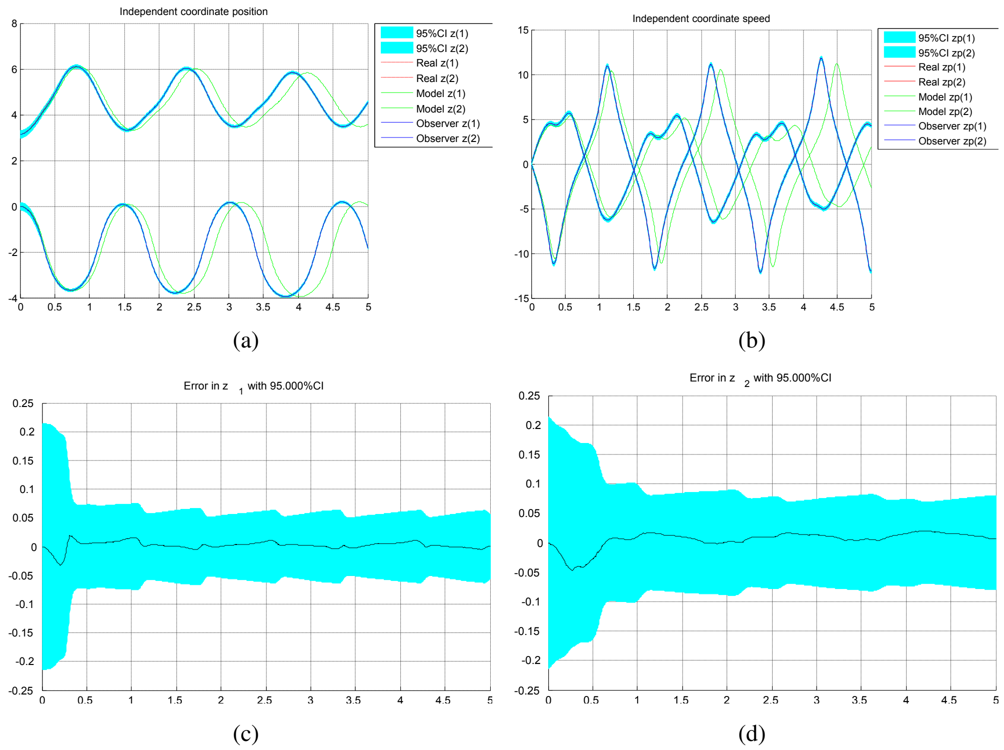

Figure 1: Representative results from the estimators benchmark presented in this work. These particular results are for the UKF algorithm applied to a five-bar mechanism. Figures show the estimated values (blue) for the two degrees of freedom of in both position (a) and velocity (b) together with 95% confidence interval and ground truth (red). Estimated and ground truth states are very close and hardly distinguishable, hence we also present the absolute errors in position (c) and velocity (d). Vertical axes are in rad and rad/s, whereas horizontal axes represent time in seconds.

these results can be compared, a batch estimator is applied to the whole history of sensor measurements, based on the non-linear optimization of the graphical model proposed in [5]. The results of these tests will be useful to discern which will be the most suitable formulation and sensor configuration for future applications.

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