



Experimental Evaluation of Interaction Force Estimators for Transparency Control of Robotic Systems

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INTRODUCTION

Transparency control can be understood as a type of control that tries to minimize the interaction forces between a human and a robot, so that the operator doesn't *feel* the robot when interacting with it. One of the main challenges of this class of controllers is that the interaction force is often not measured directly. Many studies model the human-robot coupling as a mass-spring-damper system, and then apply observers and related measurements to estimate the interaction force (Boaventura and Buchli (2016); Escalante et al. (2023)). For real systems, the stiffness and damping are also unknown. This work evaluates the performance of two interaction force estimators under unknown parameters: an Extended Kalman Filter (EKF) and a Monte Carlo (MC) estimator.

1. METHODOLOGY

Two experiments were conducted for four different spring stiffness using the IC2D test bench, described in Vergamini et al. (2023). In each experiment the human operator interacted randomly with the test bench for about 40 seconds. The interaction force is measured by the load cell (2), highlighted in Fig. (1). This measurement is used as ground truth only.

The EKF Daum (2014) implemented incorporates adaptive covariance tuning and an augmented state vector. By including the stiffness and damping of the system in the state vector the filter can converge to values that better capture the dynamics of the system. The adaptive tuning of the covariance matrices is achieved by comparing the innovation covariance of a batch of previous iterations with the current innovation covariance.

Our MC estimator Kroese and Rubinstein (2012) uses a sliding window of the measurements together with stiffness and damping values sampled within a defined range to estimate the interaction force and the system states. The mean squared error is computed, the best performing pairs are kept, and the final estimate is an average of the valid pairs.

RESULTS

The MC estimator performance relied greatly on not overestimating the upper bound of the parameters range. The EKF was insensitive to initial guesses. As shown in Tab. (1), the MC estimator demonstrated better performance overall, if the parameter range was reasonable, e.g. $[500, 8000]$ N/m for a 5 kN/m nominal value. The EKF performance degraded at higher spring stiffness, likely due to the small deflections of the spring not providing enough information to correctly update the covariances and pseudo-states.

Table 1. Comparison of MC and EKF performance in estimating interaction force under different stiffness conditions.

Attachment Stiffness		Monte Carlo			EKF		
		RMSE (N)	p-value	sampling time (ms)	RMSE (N)	p-value	sampling time (ms)
2 kN/m	Exp 1	13.47	0.00	0.0084 ± 0.1582	6.766	0.36	0.0093 ± 0.0275
	Exp 2	11.16	0.00	0.0073 ± 0.1654	8.971	0.00	0.0107 ± 0.0305
5 kN/m	Exp 1	13.84	0.00	0.0109 ± 0.1795	16.88	0.00	0.0098 ± 0.0322
	Exp 2	17.08	0.00	0.0126 ± 0.2025	17.97	0.00	0.0102 ± 0.0355
10 kN/m	Exp 1	8.021	0.00	0.0179 ± 0.2111	15.65	0.00	0.0097 ± 0.0332
	Exp 2	11.67	0.00	0.0135 ± 0.1915	23.46	0.00	0.0096 ± 0.0374
20 kN/m	Exp 1	10.29	0.00	0.0149 ± 0.1869	15.57	0.04	0.0119 ± 0.0379
	Exp 2	12.72	0.00	0.0218 ± 0.2658	20.10	0.00	0.0199 ± 0.0722

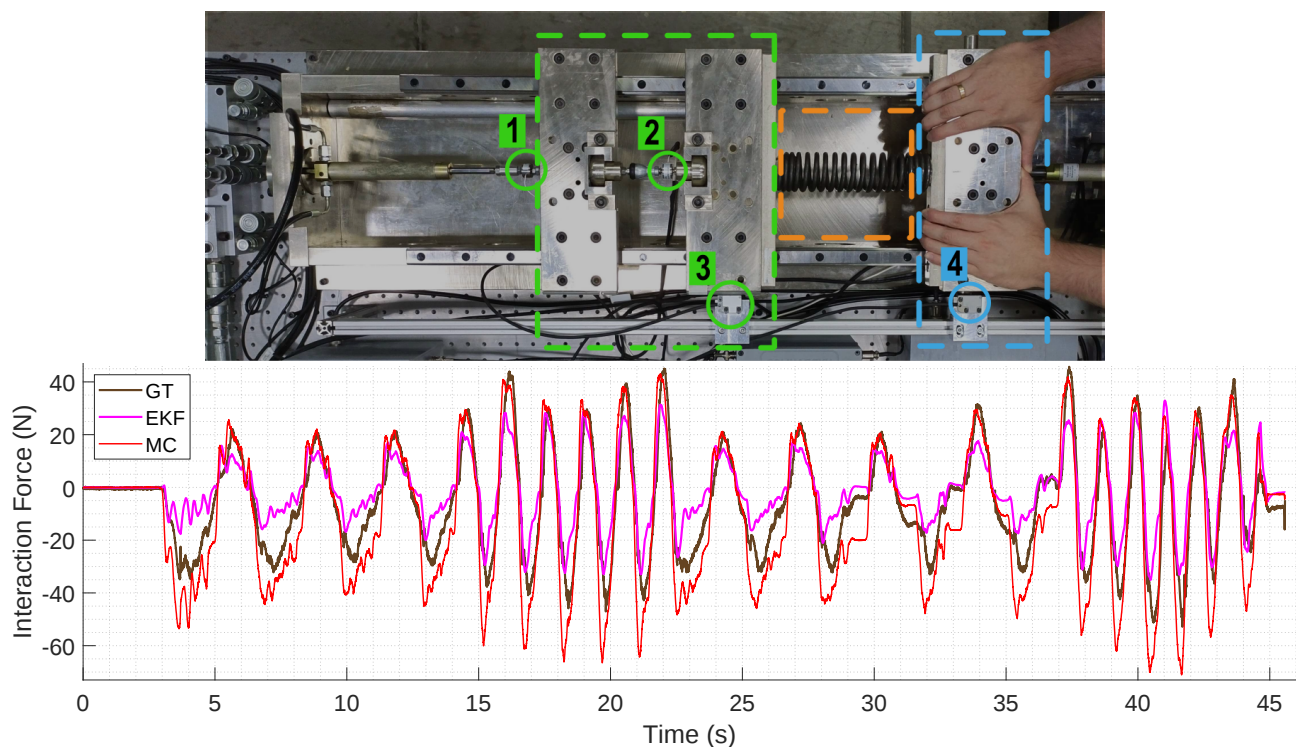


Figure 1. Experimental setup and results for the $2kN/m$ Exp 2. The robot system (green) is attached through a spring (orange), to the human (blue). (1) and (2) are force sensors, (3) and (4) are linear encoders. The real interaction force is measured by sensor (2).

CONCLUSION

For the application studied, both estimators were capable of dealing with the unknown parameters and no direct interaction force measurements. Both are fast enough to run in real-time. If there is some knowledge about the stiffness and damping of the system, the MC estimator is the better option. If there is zero knowledge about the system parameters and no ground truth to help with tuning, the adaptive EKF is more adequate, especially for more compliant attachments.

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