An Online Learning Procedure for Feedback Linearization Control without Torque Measurements: Supplementary material

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1 Additional results on GP with Gramian reconstruction

Here we analyze the performance described in the last section of the paper, to show that we achieve very good performances in linearizing the system by reconstructing the unknown dynamics. When the system is exactly Feedback Linearized it behaves as a chain of integrators, reproducing with high fidelity the acceleration commands from the MPC. This is evident in Fig. 1, where the disturbance (i.e., the unknown dynamics) is well estimated, while in Fig. 2, where no online learning is used, it doesn't occur. In Fig. 1, the learning transient cannot be appreciated. It is due to the relatively high frequency (200 Hz) with which we acquire new data and update the GP. In spite of the high frequency (high with respect to the dynamics of the system), the last acquired training data will be very close to the following query point, therefore, locally, the regression will converge very fast to the actual disturbance signal. For the same reasons, we just observe a learning transient in correspondence of discontinuous points of the disturbance, as it is evident for the joints 6 and 7 in Fig.3. Nevertheless, the GP regressor displays good performances in reconstructing the disturbance signals for all the 7 joints.

2 Gramian Reconstruction

In this section we show in simulation the effectiveness of the Gramian in estimating the joint accelerations. Numerical data shows that the approximation works very well, with a mean reconstruction error of 10^{-11}, as shown in Fig.4.

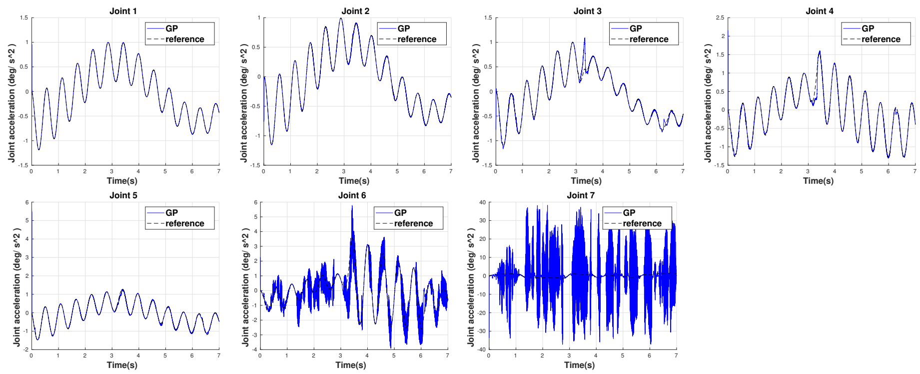

Figure 1: Acceleration profile of the corrected model with respect to the associated MPC reference.

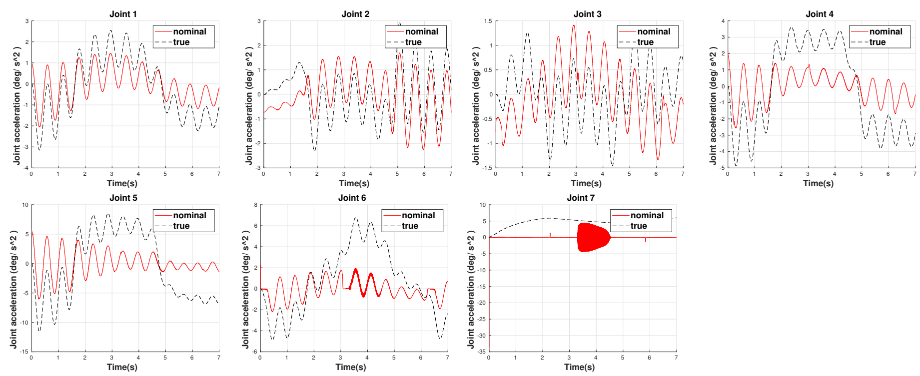

Figure 2: Acceleration profile of the nominal model with respect to the associated MPC reference.

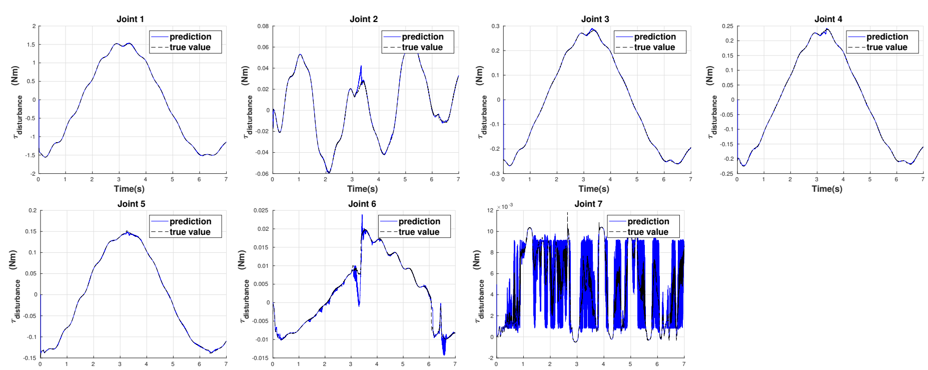

Figure 3: Prediction of the GP with Gramian reconstruction with respct to the disturbance.

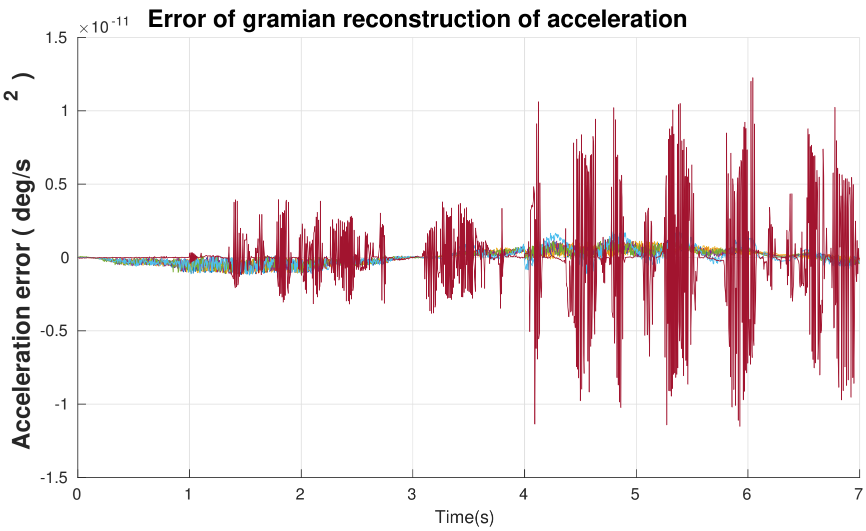

Figure 4: Difference between the real and the reconstructed acceleration for each joints.

3 Noisy torque measurements comparison

Standard inverse dynamics learning approaches define the training input as the difference between the nominal torque and the measured one. One of the main issues associated with classic methods is that they relies on noisy sensors to gather data that inevitably affect the quality of the learned models. Moreover, under certain conditions, a large sensor noise may prevent the algorithm from learning the disturbance . This is the case when the disturbance signal is smaller than the torque sensor noise

$$\hat{Y} = \tau_{measured} \pm \sigma_\tau - \tau_{nominal} \tag{1}$$

then

$$\hat{Y} = Y_{signal} \pm \sigma_\tau \tag{2}$$

where σ_τ represent the torque sensor noise, $\tau_{measured}$ and $\tau_{nominal}$ are respectively the measure and the nominal torque and $Y_{signal} = \tau_{measured} - \tau_{nominal}$. If the magnitude of σ_τ is larger than Y_{signal} it will be impossible to correctly estimate the aforementioned signal. In Fig. 5 we simulated torque sensors with a gaussian additive noise with a mean 1 and a variance 0.05. Due to the presence of noise is necessary to filter the signal. To this aim we designed a lowpass filter, with a passband frequency of $0.1\pi \cdot \frac{rad}{\#sample}$, in order to remove the high frequency components (a comparison for each joint torque between the original signal and the filtered one are shown in Fig 6). Even after the filtering operation

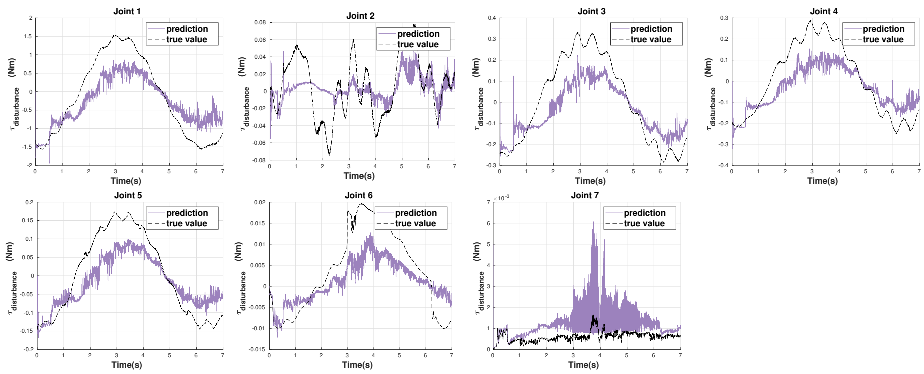

Figure 5: GPs reconstruction of the model disturbances using torque sensors. Comparing the results shown in this figure with the ones presented in Fig. 3 in this supplementary material, it's noticeable that our algorithm, relying on position measurements, outperforms the torque-based one.

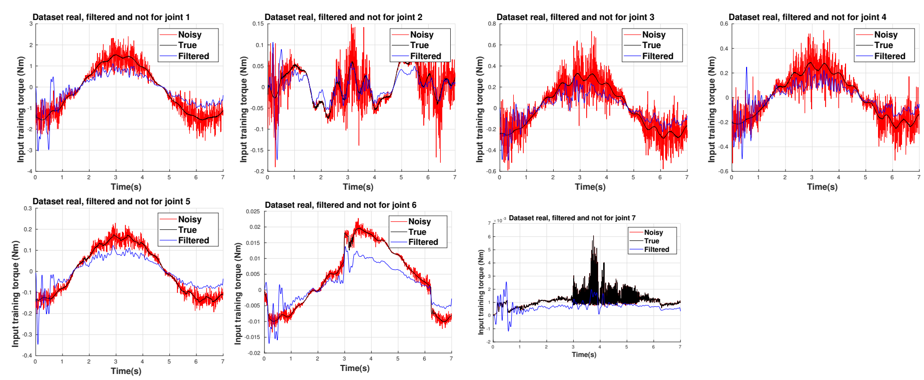

Figure 6: Comparison of dataset filtered, with noise and true values.

in Fig. 5, we can see that the prediction performances are worse than the ones obtained with our method (see Fig. 3).