Learning model-based control for lightweight robotic arms

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I. MOTIVATION

Most of the robotic arms are controlled by simple decentralized PD controllers. This control paradigm treats couplings between joints as disturbances that are to be rejected. Having a realistic model of the manipulator would allows for canceling out nonlinearities due to coupling. Furthermore, model-based controllers are able to achieve lower power consumption and compliance. This is a valuable characteristic for a lightweight robot running on batteries and operating in presence of humans. Standard rigid body dynamics (RBD) model is insufficiently precise due to elasticity of lightweight robotics arms and nonlinearities in motor drives. Recently, data driven learning techniques such as Gaussian Process Regression (GPR) have shown promising results in model learning. These methods are particaulary useful because of theirs flexibility as they learn from input-output data only.

II. LEARNING FOR LIGHTWEIGHT ROBOTIC ARMS

To learn a model suitable for control we will take a closer look at the nonlinear function linking given reference value and a robot joint state space.

$$\mathbf{q}_{ref} = f_n(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}), \tag{1}$$

where q_{ref} is the positional reference given to the inner controller and $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ is a joint state vector of the robot. By learning nonlinear mapping form the joint state space to the positional reference, we wish to enhance performance of positionally controlled lightweight manipulators. The idea is that by knowing planned joint state space trajectory $(\mathbf{q}_d, \dot{\mathbf{q}}_d, \ddot{\mathbf{q}}_d)$ and relevant nonlinear mapping $f_n(.)$, we are able to decide on input value that will ensure full joint state space tracking. We will call this value pseudo reference - $\mathbf{q}_{ps}$. Schematic drawing of this can be seen in Fig. 1. Our approach is inspired by the Torque - Position Transformer of [1], but we are interested in tracking the state space reference insted of torque reference. The other difference is that we do not need to know the details of the servo in each joint. Nonlinear function is learned based on data gathered during a motor babbling experiment. Furthermore, as the robot data is recorded continuously model can be incrementally updated during the normal operation of the system. Attention is given to different sparse and on-line methods to account for the continuos data stream. Currently, GPR is used to learn this nonlinear mapping and most appropriate covariance functions are being investigated. Proposed methods are being validated on a six degrees of freedom physical robotic manipulator (Schunk Powerball arm).

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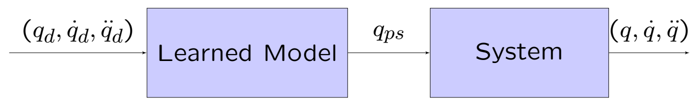

Fig. 1. Full joint state space vector $(\mathbf{q}_d, \dot{\mathbf{q}}_d, \ddot{\mathbf{q}}_d)$ is mapped to pseudo input value $\mathbf{q}_{ps}$ which serves as a reference to inner controller

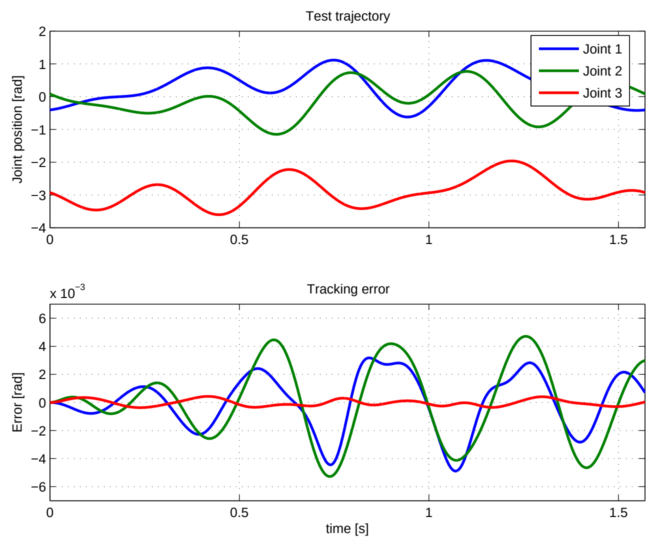

Fig. 2. Simulation results showing viability of proposed approach

III. RESULTS

Results presented here were obtained using GPR with squared exponential covariance functions with automatic relevance determination. Early simulational experiments are showing promising results. Figure 2 shows the reference trajectory and tracking error using nonlinear feedforward control. Learning was conducted using $N = 15000$ training samples and validated on differen $M = 5000$ samples. Data was collected using Robotics Toolbox on a modified Puma 560 robot using only three lower joints.

REFERENCES

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