Online Learning and Control using Sparse Local Gaussian Processes for Teleoperation

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Abstract

This work aims to achieve the goal of online model-learning and control for a teleoperation task by using Sparse Online Local Gaussian Process Regression (SOLGPR) to infer a local function mapping of robot sensor states to joint states and perform a prediction of the teleoperation command for joint control. Local Gaussian process models are learned and sparsified via Variational Inference with user-tuned bounds on model size and complexity. An optimization scheme involving periodic optimization of a drifting Gaussian process helps to reduce computation time in conjunction with the sparse local models. This framework provides a basis for a tradeoff between model complexity and performance.

1 Introduction

In the task of teleoperation, commands and sensor data are received in sequential streams, thus, in a data-driven controller, the robot model should learn and adapt to these streams of data, while also making accurate predictions about the desired motor joint inputs at pace with the operator.To this end, work in model-learning for control needs to focus on low computational-complexity and learning time while maintaining high accuracy appropriate for the task environment.

Gaussian process regression (GPR) has shown promise in modeling the inverse dynamics of robotic systems [3],however, the computational cost of training and prediction is inefficient for real-time control. Various sparse and online methods for Gaussian processes have been introduced in the literature, which usually take advantage of incremental updates to the model or finding a subset of inducing points [1] [4]. Local Gaussian process methods handle non-stationary data while maintaining low computation cost by focusing on regression in local regions of the data [2].In data retrieved from trajectories with correlated paths, drifting Gaussian process models have been suggested to keep track of a sliding window of data at a time [5]. In this work, We aim to achieve online performance of model learning by utilizing local Gaussian process models in conjunction with sparse methods to allow for a growing workspace.

2 Methods

We present Sparse Online Local Gaussian Process Regression (SOLGPR). SOLGPR handles streaming data by first partitioning each training data input/output pair (x_i, y_i) into local regions via (1) and a threshold [2].

$$w_k = exp(-\frac{1}{2}(x - c_k)^T W(x - c_k)) \tag{1}$$

These local regions are then trained using sparse variational inference for GP to select M inducing points which maximizes the KL divergence, $KL(q(f, f_m)||p(f, f_m|y))$, of the Gaussian posterior

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distributions [1]. Predictions of the function output y_p are made from the command signal x_{tel} with the trained local models according to (2), a modified version of the weighted average of each local model's predicted mean with the variance computed at each local model's prediction.

$$y_p = \frac{\sum_{k=1}^{M} w_k y_k e^{-V_k}}{\sum_{k=1}^{M} w_k e^{-V_k}} \tag{2}$$

The prediction, y_{p+1}, is used as the control input for the robot controller. The resulting state of the robot, x_{i+1}, becomes the new experience along with the control prediction (or the measured control output) for the next loop. To manage the size of the growing neighborhoods of the local models, a threshold of K local points is set as an upper bound of each region's size. For optimization, we take inspiration form [5], and employ an optimization schedule using a drifting Gaussian process.

3 Results

The SOLGPR method in this paper was evaluated using a simulated teleoperation on a planar two-link robot manipulator. Teleoperation path (2D desired positions) were generated offline and fed to the SOLGPR controller sequentially. Figure 1 shows the results of prediction on a circular path. In every loop, the training data consists of the sensed 2D position of the robot end effector paired with the joint positions of the robot. As a test of the computation cost as the data size increases, the training and prediction time for 1000 iterations was calculated and presented in figure 2.

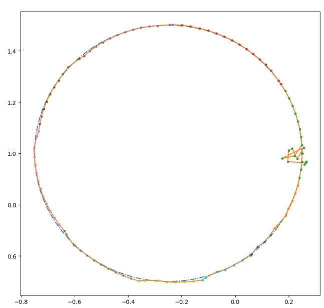

Figure 1: Trace of end effector path produced by the joint angle predictions. Different color dots represent a separate local GP model.

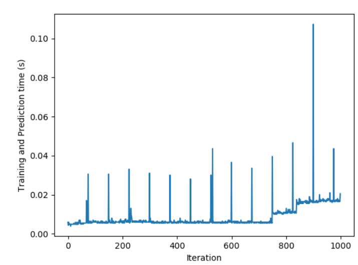

Figure 2: Time for algorithm to perform training and prediction per iteration of teleoperation signal.

4 Conclusions

The SOLGPR method realized an approach toward online model learning and control from streamed data. Computation time was kept low by implementing the strategies to tradeoff local model size and sparsity and optimizing a drifting GP periodically. However, the local model partitioning requires tuning of the distance threshold, thus some paths do not lead to accurate predictions. An optimization scheme for the tuning threshold and thereby the size of the local models would benefit this algorithm.

References

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