Local Gaussian Processes Regression for Real-time Model-based Robot Control

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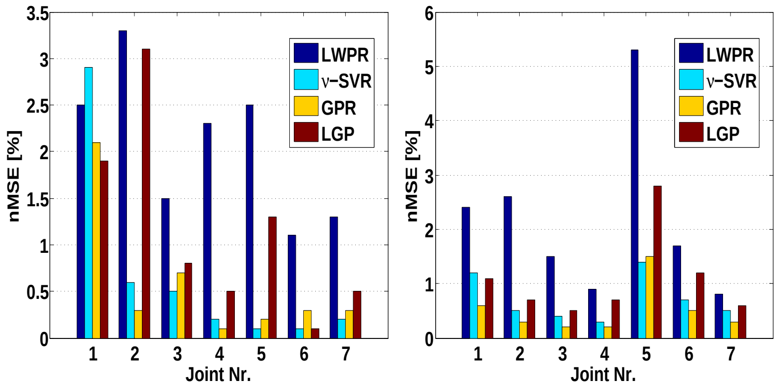
Abstract

For human motor activities, internal models can play an important role [1] representing an input-output transformation of dynamical processes in the brain to the external world. Internal dynamics models can also be used for high performance and compliant robot control [2]. However, accurate dynamics models cannot be obtained analytically for sufficiently complex robot systems [3, 4]. In such cases, machine learning offers a promising alternative for approximating the robot dynamics using measured data. This approach offers a natural framework to incorporate unknown nonlinearities as well as to continually adapt online for changes in the robot dynamics. However, the most accurate regression methods, e.g., Gaussian processes regression (GPR) [5] and support vector regression (SVR) [6], suffer from exceptional high computational complexity which prevents their usage for large numbers of samples or online learning to date. Inspired by locally linear regression techniques, e.g., LWPR, we propose an approximation to the standard GPR using local Gaussian processes models inspired by [7, 8] combining the strength of local learning, e.g., fast computation, and global regression, e.g., high approximation performance. Due to reduced computational cost, local Gaussian processes (LGP) can be applied for larger sample-sizes and online learning. Comparisons with other nonparametric regressions, e.g. standard GPR, ν-SVR and locally weighted projection regression (LWPR) [7], show that LGP has higher accuracy than LWPR close to the performance of standard GPR and ν-SVR while being sufficiently fast for online learning.

The proposed method is evaluated using real robot data generated on the Sarcos master arm and the Barrett WAM. Figure 1 shows the normalized mean squared error (nMSE) in percent of the evaluation on the test set for each of the two scenarios, i.e., the Barrett arm in (a) and the Sarcos arm in (b). Here, the normalized mean squared error is defined as: nMSE = Mean squared error/Variance of target. It can be seen that LGP generalizes well even when using only few local models for prediction. In all cases, LGP outpreforms LWPR while being close in learning accuracy to GPR and ν-SVR.

Since only a small amount of local models in the vicinity of the query point are needed during prediction for LGP, the computation time is reduced significantly compared to GPR and ν-SVR. The comparison of prediction speed is shown in Figure 2. Here, we train LWPR, ν-SVR, GPR and LGP on 5 different data



(a) **Approximation Error using BARRETT data** (b) **Approximation Error using SARCOS data**

Fig. 1: Approximation error as nMSE (in percent) for each DoF. The error is computed after prediction on the test sets with simulated data from SL-model, real robot data from BARRETT and SARCOS master arm, respectively. In all cases, LGP outperforms LWPR in learning accuracy while being competitive to ν-SVR and standard GPR.

sets with increasing training examples (1065, 3726, 7452, 10646 and 14904 data points, respectively). Subsequently, using the trained models we compute the average time needed to make a prediction for a query point for all 7 DoF. In the case of LGP, we take a limited number of local models in the vicinity for prediction as in last experiment. The time as stated in Figure 2 is the required time for prediction of all 7 DoF. Here, LWPR presents the fastest method due to simple regression models. Compared to global regression methods such as standard GPR and ν-SVR, local GP makes significant improvement in term of computation time.

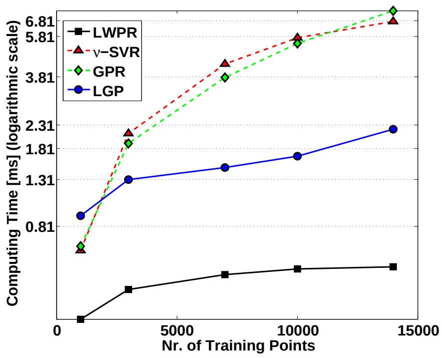


Fig. 2: Average time in millisecond needed for prediction of 1 query point. The computation time is plotted logarithmic in respect of the number of training examples.

The results show that the computation time requirements of ν-SVR and GPR rises very fast with the size of training data set as expected. LWPR remains the best method in terms of computational complexity only increasing at a very low speed. However, as shown in Figure 2, the cost for LGP is significantly lower than the one ν-SVR and GPR and increases at a much lower rate.

As seen from the Figures, LGP incorporates the strength of both local and global regressions, i.e. a tradeoff of learning accuracy and computation complexity. Using local GP, we combine the fast computation of local regression with more accurate regression methods with less manual tuning. LGP achieves higher learning accuracy compared to locally linear methods such as LWPR while having less computational cost compared to GPR and ν-SVR. The results also show that our approach is promising for an application in model online-learning which is necessary to generalize the dynamics model for all trajectories.

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