Gaussian Process based Model Predictive Control

Gang Cao

A thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in
Engineering

School of Engineering and Advanced Technology
Massey University
New Zealand

February 17, 2017

Abstract

The performance of using Model Predictive Control (MPC) techniques is highly dependent on a model that is able to accurately represent the dynamical system. The data-driven modelling techniques are usually used as an alternative approach to obtain such a model when first principle techniques are not applicable. However, it is not easy to assess the quality of learnt models when using the traditional data-driven models, such as Artificial Neural Network (ANN) and Fuzzy Model (FM). This issue is addressed in this thesis by using probabilistic Gaussian Process (GP) models.

One key issue of using the GP models is accurately learning the hyperparameters. The Conjugate Gradient (CG) algorithms are conventionally used in the problem of maximizing the Log-Likelihood (LL) function to obtain these hyperparameters. In this thesis, we proposed a hybrid Particle Swarm Optimization (PSO) algorithm to cope with the problem of learning hyperparameters. In addition, we also explored using the Mean Squared Error (MSE) of outputs as the fitness function in the optimization problem. This will provide us a quality indication of intermediate solutions.

The GP based MPC approaches for unknown systems have been studied in the past decade. However, most of them are not generally formulated. In addition, the optimization solutions in existing GP based MPC algorithms are not clearly given or are computationally demanding. In this thesis, we first study the use of GP based MPC approaches in the unconstrained problems. Compared to the existing works, the proposed approach is generally formulated and the corresponding optimization problem is efficiently solved by using the analytical gradients of GP models w.r.t. outputs and control inputs. The GPMPC1 and GPMPC2 algorithms are subsequently proposed to handle the general constrained problems. In addition, through using the proposed basic and extended GP based local dynamical models, the constrained MPC problem is effectively solved in the GPMPC1 and GPMPC2 algorithms. The proposed algorithms are verified in the trajectory tracking problem of the quadrotor.

The issue of closed-loop stability in the proposed GPMPC algorithm is addressed by means of the terminal cost and constraint technique in this thesis. The stability guaranteed GPMPC algorithm is subsequently proposed for the constrained problem. By using the extended GP based local dynamical model, the corresponding MPC problem is effectively solved.

Acknowledgements

I am deeply grateful to my co-supervisor Professor Edmund M-K Lai at Auckland University of Technology who was my primary supervisor during my first three years of Ph.D study at Massey University. His supervision is great and I am always inspired by the valuable discussions with him. He spent a lot of time on my academic writing and helped me attend several international and local academic conferences. I would not be successful in my Ph.D study without his longstanding support.

I am sincerely appreciative of Dr. Fakhrul Alam who is my primary supervisor in my last year at Massey University for his sharing of ideas and inspiration on possible applications. He helped a lot when I was preparing my thesis draft.

I wish to thank the administrators and technicians of SEAT in Massey University's Albany Campus for their countless help.

Finally, I want to thank my family for their love and support.

Contents

List of Figures

List of Tables

List of Abbreviations

ANN Artificial Neural Network

BFGS Broyden-Fletcher-Goldfarb-Shanno

CG Conjugate Gradient

CGP Convolved Gaussian Process

DGP Dependent Gaussian Process

DMC Dynamic Matrix Control

DOF Degree-of-Freedom

FM Fuzzy Model

FP-SQP Feasibility-Perturbed Sequential Quadratic Programming

GA Genetic Algorithm

GMV Generalized Minimum Variance

GP Gaussian Process

GPC Generalized Predictive Control

GPDM Gaussian Process Dynamical Model

IAE Integral Absolute Error

IDC Inverse Dynamics Control

IGP Independent Gaussian Process

KKT Karush-Kahn-Tucker

LGP Local Gaussian Process

LL Log-Likelihood

LMC Linear Model of Coregionalization

LMI Linear Matrix Inequality

LQR Linear-Quadratic Regulator

LTV Linear Time-Varying

GP-LVM Gaussian Latent Variable Model

MAE Mean Absolute Error

MAP Maximizing A Posterior

MCMC Markov Chain Monte Carlo

MFAC Model-Free Adaptive Control

MIMO Multiple-Input Multiple-Output

MISO Multiple-Input Single-Output

ML Machine learning

MLE Maximum Likelihood Estimation

MPC Model Predictive Control

mp-QP Multi-Parametric Quadratic Programs

MSE Mean Squared Error

NLL Negative value of Log-Likelihood

NLTV Nonlinear Time-Varying

NMPC Nonlinear Model Predictive Control

PCA Principal Component Analysis

PFC Predictive Functional Control

PFDL Partial Form Dynamic Linearization

PSO Particle Swarm Optimization

QP Quadratic Programming

RBFN Radial Basis Function Network

SMPC Stochastic Model Predictive Control

SQP Sequential Quadratic Programming

UAV Unmanned Aerial Vehicle