INF501 Review - Truong Nghiem

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Introduction

Model predictive control (MPC) is an excellent tool for optimizing efficiency in many dynamical systems with complex constraints. According to Dr. Truong Nghiem, this approach uses mathematical models to predict future outcomes, then optimizes a cost function to obtain control inputs on that system[1]. These inputs may be effected by user choice, exogenic factors (factors beyond the users control), or the state of the system itself. As noted by Dr. Nghiem, building control systems (the systems that monitor and supply heating, cooling, lights, and electricity) can be built efficiently and effectively with MPC. Beyond building control systems there are many possible fields that could benefit from MPC. Drone flight path stability, optimal workload assignments in open source (OS) programming communities with diverse, known, skill sets, and optimal power plant operations in an environment with an increasing number of private solar providers are topics in interest to Northern Arizona scientists.

In all of these cases, control systems depend on a model's prediction of outcomes based on various environmental factors, the requirements of the end user, and the state of the system being controlled. Such models are often expensive and difficult to develop. For buildings (and power grids), many physical and thermodynamic systems must be experimentally examined and integrated into the model. For drone flight, wind, aerodynamics, user control, and environmental hazards must all be considered. Participant interest and skill level as well as the openness of the OS community should all be considered before suggesting tasks to new developers. But collecting this information can be difficult. Worse, many of these observed conditions may change, rendering any model developed from them misleading or useless. One approach to this issue is to model the dynamical system using a Gaussian Processes (GP).

In general, GPs consider the inputs to a system to be noisy or difficult to observe. Mathematically, these inputs are considered to be a set random variables. From one perspective, a GP does not examine the specific set of inputs, but rather the variability within and correlation between inputs. This modeling of variability allows for estimation of the uncertainty in predictions. It also allows the model to incorporate prior knowledge - usually through prior distribution parameter selection. And, because the underlying uncertainty is assumed to have a normal distribution at its most fundamental level, these techniques often work well with small data sets (a claim that most machine learning methods cannot make).

MPC-GP models are constrained versions of the general GP. By imposing model structure (known fixed aspects and know random aspects), known parameter interactions, and parameter limits, a least square estimate for each time step can be produced. Then, by maximizing the amount of information (see Shannon information theory) encoded in the selected parameters at each time step, an MPC-GP model can be constructed. Using well studied estimators for model correctness like the Root Mean Square Error (RMSE) and Standardized Mean Square Error (SMSE), we can validate the trained model against known data (that was not used for training).

A further benefit of Dr. Nghiem's GP approach to MPC is that the model is easily updated since the information required to construct the model does not extend beyond the observed inputs and output. As the model begins to drift, the algorithm used to construct the model can be run again on more recent data, and the new model uploaded to the control module. This means that lengthy, expensive, labor-intensive model tuning is not necessary.

As the data sets grow larger, however, it can become computationally intractable. If the model selection process allows for fixed parameter estimation, the optimization process is a cubic function of the data size. To mitigate this problem, Dr. Nghiem proposes excluding any fixed aspect of the model. Instead, in his second (unpublished) work, he suggests and demonstrates that sufficient model complexity can be captured using the random effects alone. This alternative method, the linear Gaussian Processes (linGP-MPC), offers a considerable improvement in speed.

Since the modeling and experiments conducted by Dr. Nghiem et al. took place in the Matlab environment, it is likely that an even greater improvement in available. It would be interesting to examine the hardware requirements that such a model building process requires. If it is light enough, it may have broader applications in highly variable environments like automated vehicles.

Outside of Buildings

A significant challenge to automated drone flight is the presence of variable factors like wind and other drones. Classically derived MPC would be insufficient for such a task. However, drones often contain several state (e.g. battery charge) and experimental (e.g. lidar) sensors. Optimizing motor inputs by considering accelerometer, proximity and battery sensor readings to minimize the risk of collision and drift seems to be an obvious application of this model construction method. Further, as conditions evolve, the models could be updated quickly and easily even if the model construction requires ground-based computation.

Managing the integration of solar panels, new clean energy sources, DC power converters, and existing resources is also a problem worth tackling. This issue may not require the fast model construction that drones do, but the amount of data involved may be much larger. One of the interesting aspect of MPC-GP is that it allows for model construction based on the most informative aspects of the available data. Since the variance is the object of study, elements in the input set that are associated with the largest variance in response are likely to be the most important factors to consider when making predictions. Thus, timing the start-up or shut-down of major power generating infrastructure as well as the purchase or sale of grid power can be optimized using a carefully selected subset of grid power factors.

Conclusions

MPC-GP and linGP-MPC may be extremely useful. It stands to reason that employing powerful statistical tools in mathematically constrained systems provides much predictive power. Since buildings are rarely retrofitted for energy efficiency improvement, optimizing control systems using machine learning techniques like MPC-GP is a great idea. There are lots of control optimization problems.

Beyond control, there are lots of applications for GPs. Inference about the factors that control the transcription of DNA to mRNA can be conducted using GPs[2]. There are probably aspects of every project in the SICCS that can be more effectively explored by employing GPs.

I love them.

References

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[2] Muhammad Arifur Rahman and Neil D. Lawrence. A gaussian process model for inferring the dynamic transcription factor activity. In *Proceedings of the 7th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, BCB '16, pages 495–496, New York, NY, USA, 2016. ACM.