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Bayesian-based algorithms for Modeling and Identification for Autonomous Robotic Systems

By

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Robotics is certainly a fertile research field in which various topics from different disciplines converge, providing inter-domain solutions to practical problems. Robots are effectively employed in a great variety of scenarios, ranging from industry, medicine, agriculture and leisure, to more social and relational contexts. They come in different shapes and characteristics according to their application. To enhance the performance of robotic platforms, models started to be exploited for representing the dynamics and sometimes the robot surroundings as well. Models can be as simple as linear or take into account nonlinearities and disturbances. When models become complex to be described by means of physical laws, *e.g.* when dealing with friction, data-driven methods are used. This approach has a long history in control design, and quickly became a more complex but refined alternative to model-free approaches in robotics. In fact, learning and adapting models using the data collected during the robot operations is currently a wide-spread procedure that allows higher performance and it increases the number of scenarios in which the robot can operate. For this reason, Machine Learning methods and algorithms rapidly gained interest in robotics and it is common practice to rely on Neural Networks to train accurate and complex models using the collected datasets. Machine Learning, and more in general Artificial Intelligence, contributed to the creation of more advanced robotic platforms, and widened the spectrum of applications of robots.

The pivotal aspect in learning models is data collection. Machine Learning methods require a great amount of data, and the more complex the phenomenon to be modelled, the larger the datasets and, consequently, the higher the time needed. Training models based on Deep Neural Networks is usually carried out offline, exploiting powerful hardware without time limits. Unfortunately, when learning must happen in real-time – as in Reinforcement Learning – some limitations rise. Firstly, the amount of data collected is dependent on the time during which the robotic platforms are operating. Thus, the process

of learning is held back by the limited amount of data per unit of time that are available. Secondly, learning is a resource hungry operation. Usually, algorithms are executed on an external infrastructure, or in simulation, and only after the model is embedded into the robot. The aforementioned two limitations are particularly present when using mobile robots relying only on their computational power. This work focuses on the design and implementation of alternative formulations of the Gaussian Process Regression to cope with the constraints real-world robotic platforms have, with the objective of effectively learning the model of the environment. Similarly, the learning process is suitably customized for the application of online model learning by choosing a fast and accurate solver and setting reliable initial conditions to it. An offline data-driven dynamical model of a ground robot is learnt to demonstrate the good performance of Gaussian Process Regression. A framework for online modelling of the environment is presented and tested onto a real-world robot to assess its performance in presence of the aforementioned limitations, showing good modelling capabilities and fast runtimes.