When Machine Learning meets Robotics and Optimal Control

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Optimal control [Lib11] is a useful and versatile framework allowing to control a broad class of dynamical systems described by an ordinary differential equation, while seeking to minimize a given cost function (energy consumption of the system, time to reach a given goal, etc.). This technic has been successfully applied to many challenging problems, such as in aerospace industry, robotics, neurophysiology, etc.

But, optimal control is now facing new troubles: it seems hard or even impossible to precisely determine their governing equations (the model of the system) for some dynamical systems because the physical phenomena involved are too complicated or poorly understood. To get around this issue, recent control approaches combined with some machine learning techniques have tried to directly learn this dynamical model from the measurements of the systems (the data coming from the sensors): the so-called Koopman framework [BMM12; WKR15; KM18].

In this work, we propose to leverage this Koopman framework in the context of robotics to first learn the dynamical model of a sophisticated robot and second, to control it by exploiting this approximated model. At the end of this work, it will even be possible to illustrate the effectivity of this pipeline directly on a real humanoid robot located at LAAS-CNRS in Toulouse.

References

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