Dealing with challenging robots, environments and missions: operational space control in the context of motor learning

Vincent Padois

I. Introduction

Robotics has evolved from an industrial, repetitive framework to application domains with much more variability of tasks and increasing complexity in uncertain environment. This is clearly the case for Service Robotics where the safety of the interactions is also a major issue.

Based on these observations, part of the research activities of the *Motion & Perception* group at the *Intelligent Systems and Robotics Institute* (ISIR) from *Université Pierre et Marie Curie* (UPMC) is dedicated to human motion analysis and to motion generation and control for humanoid robots.

This abstract gives a quick overview of the approach we are working on to solve the problem of motion generation and control for humanoid robots. It also tries to show how our approach relates to the existing literature in the domain and why it seems to be a promising alternative within the framework of Service Robotics and more generally in the context of humanoid robots evolving in uncertain environments.

II. Background

Humanoid robots are highly redundant, tree-structured, poly-articulated systems for which motion generation strategies and techniques are being developped using model-based control either using reactive approaches as in [4] or planning based techniques as in [8].

These approaches offer a well fitted framework to describe tasks in a hierarchical manner and to handle the numerous constraints associated to human(oid) motions. These constraints are either related to the motion of the system itself: joint limits, balance or to its evolution in the environment: multi-contacts, obstacle avoidance.

However, they assume good models of the system's velocity kinematics and dynamics as well as a good model of the environment. These are strong assumptions and, as a consequence, efficient control of such systems requires either accurate models or control approaches that perform well in the presence of model inaccuracies.

One way to obtain accurate models of a robot is through expert system identification. This process is all the more difficult and time consuming that the mechanical structure of the robot is prone to frictions and multiple sources of noise. In fact, even if good models can be obtained, they cannot account for uncertainties related to the knowledge of the environment as well as for those related to the dynamic aspect of the mission realization. Thus, one need a way to take these uncertainties into account while still being able to benefit from the well-suited framework offered by model-based control approaches.

In order to reach this goal, we propose an approach using reactive model-based control within the framework of Operational Space Control ([1]) as well as incremental model learning techniques. Incrementally learning the models required for the control of the system allows to take some usually non modelled effects into account as well as to adapt to changing conditions in the mission realization.

The next section briefly introduces how we combine Operational Space Control as well as model learning techniques.

III. Model based control using learnt models

Operational Space Control regroups a set of control techniques relating, in a linearised fashion, the task space (ie. the space where the task is naturally described (hand, eyes, COG)) to the joints space. This linear relation can either be described at the velocity level using the effector Jacobian matrix or at the dynamics level using the projection of the dynamics of the system in the task space using the system's Jacobian.

Such a description allows the use of Linear Algebra tools and a Jacobian inverse can then be used to compute joints velocities or torques given desired task twists or wrenches. In the case of redundant systems, there exists an infinity of solutions to the Jacobian inverse problem and one can choose among this infinity in order to satisfy other tasks or constraints. Tasks and constraints can be hierarchically ordered using projectors on the null space of each task.

We propose to incrementally learn the various relations allowing the control of redundant systems using the Operational Space Control. To do so, we use LWPR ([7]). LWPR is a function approximator which provides accurate approximation in very large spaces in a $O(m)$ complexity, where m is the number of sample data. We use it here to learn both the direct geometric model and velocity kinematics (Jacobian) model of our robot.

LWPR uses a combination of linear models, which are valid on an elliptic zone of the input spaces. The model strength is weighted by a Gaussian curve. This space may evolve during training to match the training data. Each model is called a receptive field (RF). The prediction of an entire

V. Padois is Assistant Professor of Computer Science and Robotics at Université Pierre et Marie Curie (UPMC) - Institut des Systèmes Intelligents et de Robotique (ISIR).
Contact: `vincent.padois@upmc.fr`
Address: UPMC - ISIR
4 place Jussieu - Boite Courrier 173
75252 Paris Cedex 05
France

LWPR model on an input vector is the weighed sum of the results of all the active surrounding RFs.

The RFs of a model are created when new input data is not part of any existing RF. Conversely, when a field overlaps another, it is deleted.

Each RF first projects the input vector on the most relevant dimensions for estimating the output vector by using Partial Least Squares [5]. During each update, the projector is updated and the algorithm checks whether increasing the complexity by adding another dimension to the input projection significantly reduces the estimation error. If it is so, it modifies the projector accordingly. The projected vector is then used in the n dimension linear model (n being the output dimension) to give the output of the RF.

During prediction with an input vector, the distance between the vector and the receptive fields area is tested for activation and only the significant RF are activated

IV. Work in progress

We have successfully implemented an Operational Space Control scheme using a learnt Jacobian in simulation on a planar mannequin realizing a crouch-to-stand task task ([3]) as well as on a *Bioloid* (see figure 1), a toy-like humanoid robot ([6]).

Fig. 1. A picture of the Bioloid assembled as a humanoid robot

We are now working in simulation on the combination of multiple tasks including balance of the mannequin. This requires to build projectors on the null space of the different tasks which can be computationally expensive since an inverse of the Jacobian has to be computed at each control step. We are planning to learn this inverse in order to reduce the associated computation time.

We also would like to port our simulation work to the real world case on the iCub robot (see figure 2) which is present in our lab.

Finally, we are investigating the efficient learning of the dynamics model of humanoid robots using LWPR.

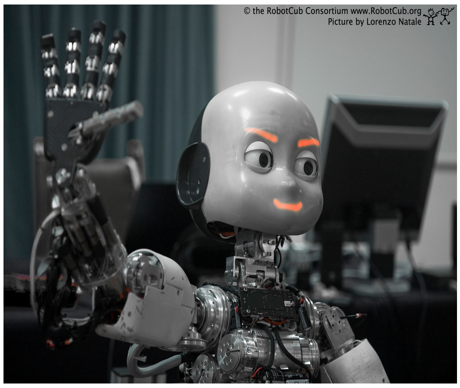

Fig. 2. The iCub robot

V. Conclusion

This abstract gives a brief overview of our activity in the domain of motion generation and control for humanoid robots. Our method is based on the use of incrementally learnt models within the framework of Operational Space Control. It seems to be a promising approach within the context of Service Robotics where robots evolve in unknown, dynamics environment.

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The author also gracefully thanks the RobotCub consortium ([2]) which provided UPMC - ISIR with an iCub robot on which most of the presented work will be tested.

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