Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 7 (2011) 166–168

Procedia Computer Science

The European Future Technologies Conference and Exhibition 2011

Impact of Body Parameters on Dynamic Movement Primitives for Robot Control☆

Naveen Kuppuswamy [1], Cristiano Alessandro [1]

Institute for Informatics, University of Zurich, Zurich, Switzerland

Abstract

The problem of movement coordination in large DoF (Degree of Freedom) robots is complex due to redundancies. In this regard, Dynamic Movement Primitive (DMP) is a useful planning technique, inspired by biology, that can be used to store and reproduce trajectories about every DoF. This work is a preliminary study that aims to understand and quantify the influence of the robot dynamics upon the performance of DMP in a simulated 2DoF robot arm. The investigation demonstrates that the effect of the robot body dynamics needs to be taken into account during the learning process of the DMP.

Selection and peer review under responsibility of FET11

Keywords: Dynamic movement primitives; robot dynamics

1. Introduction

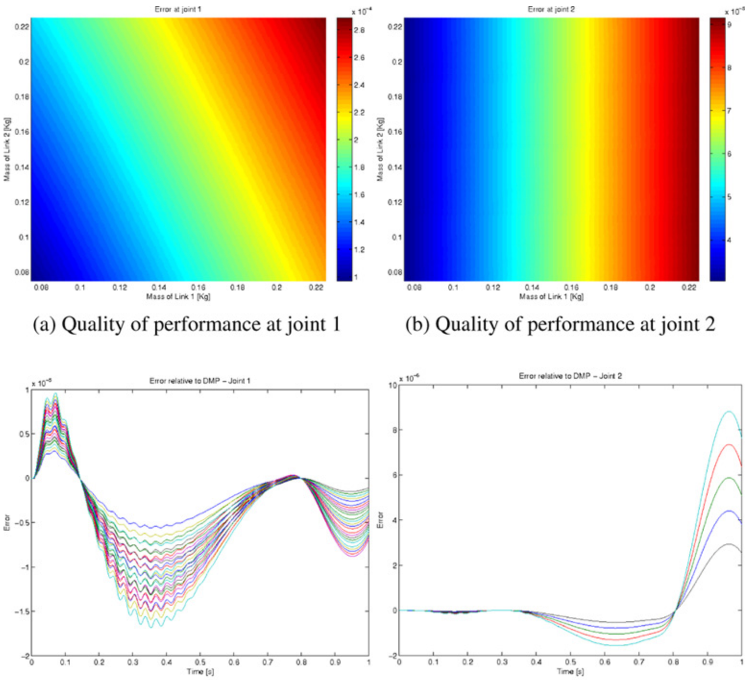
Movement coordination for compliant robots with a large number of DoF is a very difficult task and necessitates some form of planning. Due to the high number of DoFs and the almost infinite possible ways of using them over time, an infinite number of possible movement plans might exist for any given task. While this in itself can be advantageous from the redundancy perspective, from a learning point of view, finding good movement plans is complicated; computationally, well known statistical learning techniques do not scale well to problems characterized by a high dimensional state space (i.e. curse of dimensionality).

As proposed in the field of human motor control [1], an alternative method of constraining movement planning might be possible by requiring that movements are built from basic building blocks. Dynamic Movement Primitive (DMP) [2,3], is a technique that allows movement plans to be encoded and reproduced with a set of parameters, that can be learned using regression based methods [4]. The DMP architecture consists of controllers based on nonlinear dynamical systems, and using locally weighted regression techniques to learn complex, discrete or rhythmic, movements from a training trajectory. The controllers can be considered to be discrete or rhythmic pattern generators which can replay and modulate the learned movements, while being robust against perturbations.

Despite numerous demonstrations in recording and reproducing movement plans in a wide variety of robots, the impact of body dynamics on the performance of DMP and trajectory learning is not yet well understood. This issue is crucial when we consider the challenge of accurate joint level control of compliant robots [5]. This work focuses

☆ This research has been supported by the EU project RobotDoc under 235065 from the 7*th* Framework Programme, Marie Curie Action ITN.
E-mail addresses: naveenoid@ifi.uzh.ch (N. Kuppuswamy), alessandro@ifi.uzh.ch (C. Alessandro).
[1] The Authors would like to thank Prof. Auke Ijspeert and Mr. Mostafa Ajallooeian of EPFL, Lausanne, Switzerland for their input.

Selection and peer review under responsibility of FET11 doi:10.1016/j.procs.2011.09.068



(a) Quality of performance at joint 1 (b) Quality of performance at joint 2

(c) Relative error at joint 1 (d) Relative error at joint 2

Figure 1. DMP performance for a 2DoF planar robot tracking a horizontal line trajectory (w.r.t gravity).

in quantifying the relationship between body parameters and performance of the DMP in controlling the robot, and it aims at demonstrating the need for incorporating body dynamics into the DMP learning framework.

2. Simulation Experiments and Results

The simulator used consisted of a 2DoF planar robot arm coupled with a DMP for each joint. The DMPs are trained using locally weighted regression [4] and the robot contains appropriately tuned PID controllers at the joint level. The training trajectories at the joint level were obtained from inverse kinematics of (a) a horizontal straight line, (b) a vertical line, and (c) a spiral moving upwards (all w.r.t gravity). On a uniform distribution of masses at the 2 links, 25 different candidate robots were defined for the experiments.

The tracking performance for each of these trajectories was analyzed at each joint by means of a quality measure Q. This was defined as the root-mean squared distance between the joint trajectory learned by the DMP and the one performed by the robot. Results are presented in Fig. 1a and Fig. 1b for each of the candidate robots with the task of tracking a horizontal line. The results indicate that errors decrease with mass, and therefore they are due to the dynamics of the robot (i.e. a ideal massless robot has the best error performance). Further, the variation in mass of link 1 has a greater impact then the variation in mass of link 2 on the error performance.

The plots in Fig. 1c and Fig. 1d depict the tracking errors as a function of time for each of the 25 robots. Reflecting the Q performance results, candidates with the least mass present the lowest error. An interesting qualitative aspect to the performance is the presence of zero-crossover points independent of the robot mass; independently of dynamic effects, there exist certain points in time unique to a training trajectory where the errors drop to zero.

3. Conclusions and Future Work

In this an analysis of the Dynamic Movement Primitive with regards to the impact of a robot's body parameters was presented. First, the relationship of the DMP with the relevant neuroscientific concepts of muscle synergy and central pattern generators was discussed. We then presented a simulator of a 2DoF planar arm wherein we tested the DMP performance with respect to the mass of the robot's links. The results indicate the need to incorporate the body dynamics into the learning phase. Future work would be to develop and quantify the performance of such a technique in a real compliant robot.

References

[1] A. D'Avella, P. Saltied, E. Bizzi, Combinations of muscle synergies in the construction of a natural motor behavior, Nature Neuroscience 6 (3) (2003) 300–308.

[2] S. Schaal, P. Mohajerian, A. Ijspeert, Dynamics systems vs. optimal control – a unifying view 165 (2007) 425–445. doi:DOI: 10.1016/S0079-6123(06)65027-9. URL http://www.sciencedirect.com/science/article/B7CV6-4PV8M5N-11/2/8174c368654a9f13f32d1976026a5302.

[3] A.J. Ijspeert, J. Nakanishi, S. Schaal, Learning attractor landscapes for learning motor primitives, in: Advances in Neural Information Processing Systems, MIT Press, 2003, pp. 1523–1530.

[4] C.G. Atkeson, A.W. Moore, S. Schaal, Locally weighted learning for control, Artificial Intelligence Review 11 (1997) 75–113, 10.1023/A:1006511328852. URL http://dx.doi.org/10.1023/A:1006511328852.

[5] A. De Luca, Feedforward/feedback laws for the control of flexible robots, in: IEEE International Conference on Robotics and Automation (IROS), Vol. 1, IEEE, 2000, pp. 233–240.