Generalization of Biped Locomotion Tasks with Dynamic Motion Primitives

José Rosado, Filipe Silva, Vítor Santos

Abstract— **In recent years, several studies have suggested that improved performance of modern robots can arise from encoding commands in terms of motor primitives. In this context, dynamic movement primitives (DMP) appeared as a powerful tool for motion planning based on demonstration examples. This approach is currently used as a compact policy representation well-suited for robot learning. In this work, we focus on an important ability of humanoid robots employing DMPs as open-loop trajectory representations: the generalization of learned walking movements from a single demonstration. The goal is to demonstrate and evaluate how new movements can be generated by simply modifying the parameters of rhythmic DMPs learned in task space. The formulation in task space allows recreating new movements such that the DMP's parameters directly relate to task variables, such as step length, hip height, foot clearance and forward velocity. The study is performed using the V-REP simulator, including the adaptation of the humanoid robot's gait pattern to irregularities on the ground surface.**

Keywords— Biped locomotion, motor primitives, movement generalization, single demonstration.

I. INTRODUCTION

Humanoid robots have been developed to operate in real world environments and to deal with a variety of complex tasks. Developing the full potential of these robots is only possible by giving them the ability to reproduce, generalize and learn a given task. In this context, there is an increasing need to move away from robots that are pre-programmed explicitly towards those endowed with learning and adaptation abilities. The expected interaction and cooperation among humans and robots imposes additional restrictions in terms of movement appearance, promoting those that look natural and predictable. In this line of thought, a large body of research has been dedicated to the use of human motion capture systems for extracting observed poses as input for teaching robots to perform from simple movements to complex skills.

However, there are several challenges when transferring skills from humans to robots [1], [2]. The first challenge is to understand the principles governing human movement coordination in order to select the most appropriate methodology to encode the observed example trajectories. Second, the motion planning approaches based on demonstrated examples require the evaluation of their ability to generalize to new situations. This means the ability of the robotic system to generate trajectories with similar kinematics and/or dynamics in areas of the work volume not covered during the training phase.

Problems associated with learning biped walking behaviors from human data have been addressed using different frameworks, number of examples and tasks [3-5]. In this work, we focus on the problem of generalizing from a single demonstration in the specific task of biped locomotion. Here, rhythmic DMPs are employed as open-loop trajectory representations. The main purpose is to evaluate how new movements can be generated by simply modifying the parameters of DMPs learned in task space. The generalization capability, which is the main focus of this paper, was studied and evaluated using an ASIMO [6] robot model in the V-REP simulation software [7].

The remainder of the paper is organized as follows: Section II describes the proposed approach based on DMPs learned in the task space. Section III describes the experiments performed in this study. Section IV concludes the paper and discusses future work.

II. METHODS

The control of biped locomotion is a challenging problem mainly due to its nonlinear, multivariable and unstable dynamics. Additionally, there are two inherent characteristics of biped robots playing a key role in planning and control, namely the limited foot/ground interaction (unilateral constraint) and the discrete changes in the dynamics (time-varying dynamics) during the walking cycle as the system changes between single and double-support phases. A commonly used control approach is to compute in advance desired motions using some form of pattern generator formulation (*e.g.*, parameterized curves, optimization of some metric) or by acquiring teacher demonstrations aiming to transfer skills from humans to robots. This desired motions are then replicated and

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modified online through feedback (*e.g.*, according to a ZMP-based control law) in order to maintain the dynamic stability.

Given the importance of autonomous behavior, humanoid robots are being designed more and more using neurobiological knowledge. In line with this, different approaches have been proposed in the robotics community for the representation of discrete and rhythmic movements. Dynamical system motor primitives have become a robust policy representation that facilitates the process of acquiring and improving the desired behavior [8]. The basic idea behind DMPs is to use an analytically well-understood dynamical system with convenient stability properties and modulate it with nonlinear terms such that it achieves a desired point or limit cycle attractor. The methodology transforms simple attractor systems with the help of a learnable forcing function term. The approach was originally proposed by Ijspeert *et al.* [9] and, since then, other mathematical variants have been proposed to generate discrete and periodic movements [10].

DMPs exhibit a desirable property in the context of robot learning from demonstration: the system does not depend on an explicit time variable, giving them the ability to handle spatial or temporal perturbations. This property makes them attractive in order to create smooth kinematics control policies that can robustly replicate demonstrations. Additionally, its formulation includes a few parameters which allow changing the learned desired behavior. These parameters can potentially be used to adapt the learned movement to new situations in order, for example, to adapt the final goal position, the movement amplitude or the duration of the movement. However, the adaptation of these primitives to new situations becomes difficult when the demonstrated trajectories are available in the joint space. The problem occurs because, in general, a change in the primitive's parameters does not correspond to a meaningful effect on the given task. This becomes an even more important concern for robots with many degrees-of-freedom (DOF).

In this work, rhythmic DMPs are used for representing biped locomotion movements. The DMPs are formulated for each coordinate *X*, *Y* and *Z* of the two feet in task space, considering that the reference coordinate system is placed on the robot's hip section. This accounts for a total of six DMPs whose outputs are converted, through an inverse kinematics algorithm, to the desired joint trajectories used as reference input to the low-level feedback controller. Table I summarizes the standard formulation used for describing each individual DMP. The periodic walking cycle is characterized by the amplitude of the oscillator, *r*, the frequency of oscillation, ω, and the offset, *g*.

TABLE I: DEFINITION OF THE RHYTHMIC MOVEMENT PRIMITIVES

Dynamical system	$\tau\dot{z} = \alpha_z[\beta_z(g-y)-z]+f$ $\tau\dot{y} = z$
Canonical system	$\boldsymbol{\tau\dot{\phi} = \omega}$
Forcing term *f*	$f(\phi,r) = \dfrac{\sum_{i=1}^{N}\psi_i\varpi_i}{\sum_{i=1}^{N}\psi_i}r$ $\psi_i(x) = \exp(-h_i(\cos(\phi-c_i)-1))$

The forcing function is dependent on the oscillatory canonical system and the exponential functions ψ_i are von Mises basis functions. Phase coordination between legs is provided by the canonical oscillators such that the left and the right limbs move 180 degrees out of phase. Based on this formulation, the main goal is to evaluate how new movements can be generated by simply modifying the parameters of rhythmic DMPs learned in task space. Therefore, the amplitude, frequency and offset of the learned walking pattern should be modified by scaling the corresponding parameters *r*, ω and *g*, respectively,

As stated before, the motion planning is accomplished by learning the Cartesian trajectories of the lower extremities of both feet (see Fig. 1 and Fig. 2). The proposed formulation allows generating new movements such that the DMPs' parameters of each coordinate directly relate to task variables, such as step length, hip height, foot clearance and forward velocity. Furthermore, these locomotion variables are directly related with a set of high level motion goals, such as for example: (*i*) to maintain a constant forward velocity or, alternatively, to apply a small horizontal oscillation, (*ii*) to maintain a constant hip height or, alternatively, to apply a small vertical oscillation, (*iii*) to place the foot on the ground with zero velocity in order to reduce the impact effects and (*iv*) to lift the foot above the ground to avoid obstacles.

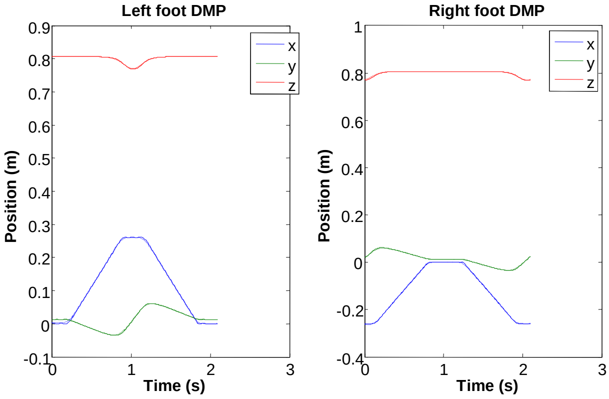

Fig. 1: Left and right foot trajectory as seen from the robot's reference coordinate system.

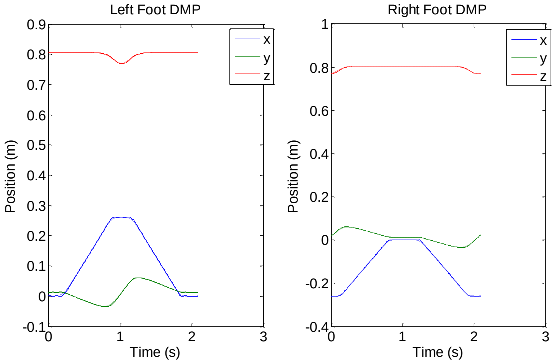

Fig. 2: Left and right foot trajectory over a period superimposed with the modulated DMP.

The benefits of the DMP modulation and generalization in task space were also verified in [11], in which the results show a lower generalization error.

III. NUMERICAL SIMULATIONS

Several experiments have been conducted to demonstrate the generalization of biped locomotion by changing the parameters of the learned DMPs. Here, two specific experiments are performed and the achieved results are discussed. The first experiment aims to evaluate the generalization from a single demonstration. The second experiment evaluates the robustness of changing the parameters of the learned DMPs by testing walking over a surface with irregularities in the form of small steps. In any case, numerical simulations are performed using an ASIMO model already available in the V-REP simulator library.

A. Generalizing from a single demonstration

First, we test the DMP approach trying to answer the following question: can the coordination of joint motions obtained from motion primitives fitted to one particular gait pattern be used to generalize to other situations? The intention is to maintain the overall style of the demonstrated movements and its stable condition by a simple change of DMP parameters. On the one hand, since the DMPs are modulated in the task space, movement generalization can be easily performed by directly varying the DMP parameters, such as the amplitude (r), the starting (y_0) or the goal position (g). On the other hand, since the feet coordinates are obtained in a referential located on the robot's hip section, this means that the corresponding trajectories are periodic function of time. As a result, the amplitude of the oscillators represents the step length, the foot clearance and the hip height, depending on the coordinate axis.

In this subsection, we assess how well the humanoid robot reproduces and generalizes a gait pattern from a single demonstration. The demonstration example takes into account domain knowledge, such as task-relevant parameters and stability conditions. The generalization performance uses a metric defined in the Cartesian space to evaluate the deviations in the trajectories of each foot. More specifically, this metric is defined as the root-mean-square error between the original movement performed for a given step length and forward velocity and the movement that results from generalizing the learned DMPs from a single demonstration (for the same step length and forward velocity parameters).

Fig. 3 shows the results of the root-mean-square error between the original and the generalized movements expressed in terms of the circles radii (min average error is 2.7mm and max avg. error is 2.65cm). These errors are evaluated for different step lengths and forward velocities. In this figure, the black circle represents the base DMP used for generalization. We can see that a change on speed has small effect on the error measure. On the other side, changing the step length has a significant influence on the error, which increases with larger steps.

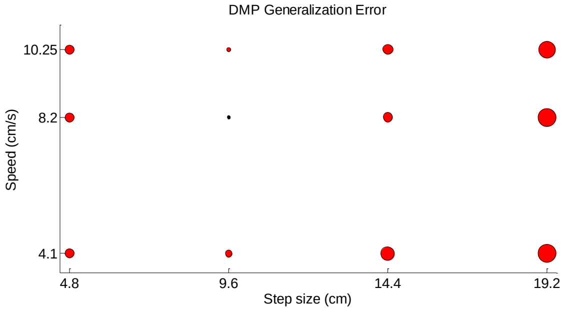

Fig. 3: Errors between the original movement and the generalization of the learned DMP for different step length and forward velocity parameters (error is scaled by 10, for representation purposes).

B. Robustness on uneven ground

Biped walking in irregular grounds depends on prediction about when the swing foot touches the ground. Hence, the robot's behavior need to be modified online and the learned movement representation (its global shape) need to be adapted during the execution so that the robot can maintain its postural stability. Based on the same approach, we adjust online the DMPs parameters in order to properly incorporate this event-dependent behavior, while maintaining the overall movement's duration. The appeal is that most humanoid robots have available ground contact information at the instant of impact of the swing foot with the ground.

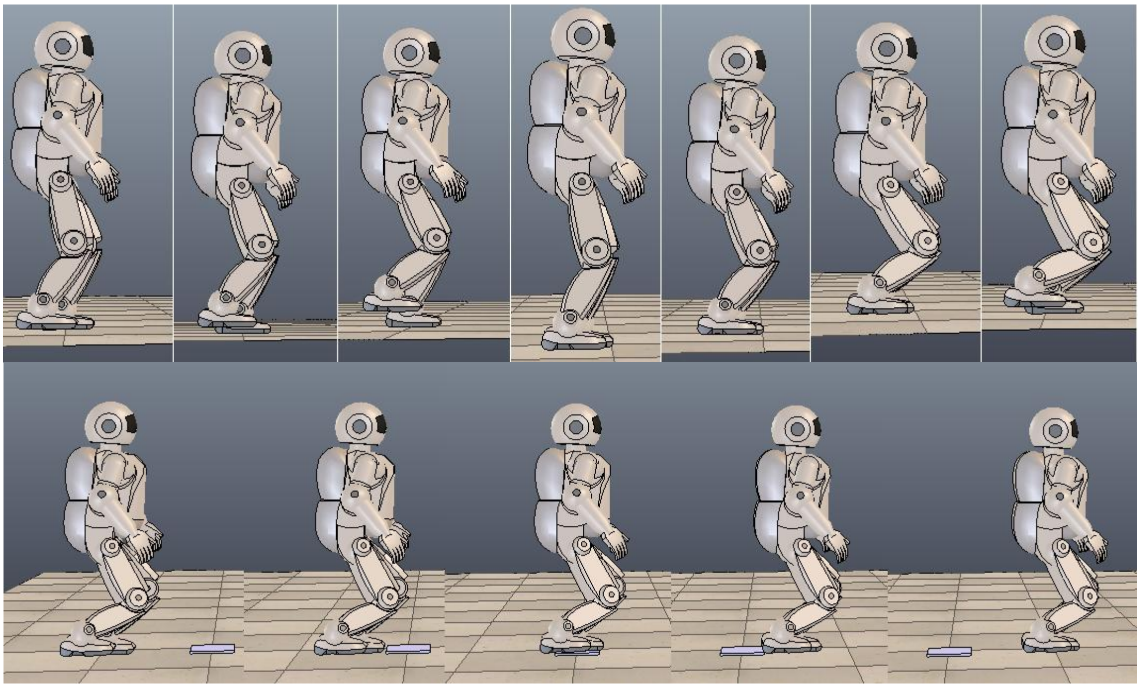

Fig. 4: Snapshots of the robot’s configuration for different locomotion parameters (up) and snapshots of simulation walking on uneven ground (bottom).

Fig. 4 illustrates the adaptation of biped walking over a ground surface (unknown to the robot) with an irregularity in the form of a small step. The online adjustment of the DMPs parameters retains the advantages of the original formulation and performs robustly with small irregularities that, anyway, approximate well real environments

IV. CONCLUSIONS

In this paper, we presented a study and evaluation on the possibilities of generalization of biped locomotion with DMPs modulated from a single movement. More specifically, we use rhythmic DMPs learned in the task space that directly relates to locomotion parameters, such as step length, hip height, foot clearance and forward velocity. Numerical simulations show that the proposed formulation is well-suited for biped locomotion, namely to achieve robust steady state walking in uneven grounds. Further study is in progress to include a feedback term on the DMP formulation that will allow achieving better adaptation to new situations. Future work will address the capture of human motions with a VICON system.

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