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Extraction of primitive representation from captured human movements and measured ground reaction force to generate physically consistent imitated behaviors

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ABSTRACT

In this paper, we propose an imitation learning framework to generate physically consistent behaviors by estimating the ground reaction force from captured human behaviors. In the proposed framework, we first extract behavioral *primitives*, which are represented by linear dynamical models, from captured human movements and measured ground reaction force by using the Gaussian mixture of linear dynamical models. Therefore, our method has small dependence on classification criteria defined by an experimenter. By switching primitives with different combinations while estimating the ground reaction force, different physically consistent behaviors can be generated. We apply the proposed method to a four-link robot model to generate squat motion sequences. The four-link robot model successfully generated the squat movements by using our imitation learning framework. To show generalization performance, we also apply the proposed method to robot models that have different torso weights and lengths from a human demonstrator and evaluate the control performances. In addition, we show that the robot model is able to recognize and imitate demonstrator movements even when the observed movements are deviated from the movements that are used to construct the primitives. For further evaluation in higher-dimensional state space, we apply the proposed method to a seven-link robot model. The seven-link robot model was able to generate squat-and-sway motions by using the proposed framework.

1. Introduction

Imitation learning is one major research topic in neuroscience, especially after the remarkable neural activities related to imitation learning observed in monkey brains. Neurons in the monkey premotor cortex (area F5), called the mirror neurons are activated not only when a monkey observes a specific behavior but also when it generates the same behavior (DiPellegrino, Fadiga, Fogassi, Gallese, & Rizzolatti, 1992).

Behavioral science has also focused on imitation learning, a skill acquisition strategy in which skills are learned by observing demonstrator behaviors. Imitation learning, which is a learning strategy that can only be executed by animals with higher intelligence, is considered an efficient way to control high-dimensional systems, e.g., the human body, with many sensors and actuators (Schaal, 1999).

Thus, in recent years, attention has been directed to imitation learning in humanoid robotics. For humanoid robots with many degrees of freedom, a considerable amount of time is required to prepare multiple motions in advance since the number of combinations of joint angle trajectories is quite large. Imitation learning is considered as a suitable approach to initialize parameters in vast search space (Calinon, Guenter, & Billard, 2007; Nakaoka, Nakazawa, Yokoi, Hirukawa, & Ikeuchi, 2003).

However, directly using demonstrator motion trajectories often fails because of the differences between the physical properties of the demonstrator and the robot. For example, a humanoid robot might fall over or hit its own body with its hand if it directly copies the corresponding joint trajectories of a demonstrator's behavior.

On the other hand, by simply watching a demonstrator's movements, humans can imitate a motion without falling over, even if their physical properties differ from those of the demonstrator. This issue is related to the mind-reading problem. Mind-reading is the ability to estimate other individual's mental states by adopting one own perspective (Gallese & Goldman, 1998). Mirror neurons are considered as a key element to understand mind-reading (Gallese & Goldman, 1998). Similarly, it is supposed that humans

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take their own dynamics into account when they are imitating demonstrator behaviors. Assuming that imitated movements are not identical to the demonstrator's behaviors for the reason described above, the question remains: how are the observed behaviors converted to imitated actions? The concept of movement primitives is one key idea to explain this conversion (Demiris & Hayes, 2002; Wolpert & Kawato, 1998). Movement primitives are components that can generate action sequences to accomplish goal directed behaviors (Schaal, Ijspeert, & Billard, 2003).

In this study, we propose to use the primitive representations in switching state-space models (SSSMs) (Ghahramani & Hinton, 2000) to convert an observed movement sequence to a physically consistent motion for a robot model through estimating the ground reaction force (GRF) profile. By using SSSMs, we can represent a variety of movements by combining primitive representations, while using one large-scale nonlinear dynamical model (e.g., Wang, Fleet, & Hertzmann, 2008) to represent many different human behaviors would be computationally impractical. The parameters of the linear dynamical models in SSSMs are determined from the captured human behaviors and the simultaneously measured GRF. Therefore, our approach does not need to explicitly define the segmentation criteria to extract primitives from a measured motion sequence. By using SSSMs, we show that the robot can generate newly observed movements that are, in some extent, different from the movements used to learn the parameters of the linear dynamical models. We also consider balance control by estimating GRF from the captured human's motions. GRF is rescaled by the weight ratio between a demonstrator and a robot. This procedure is consistent with the idea of mind-reading, which is the ability to estimate another individual's mental state by adopting one's own perspective. We use GRF to generate proper interaction between robots and environments to imitate demonstrator behaviors.

We use the GRF profiles generated by the demonstrator rather than calculating GRF profiles that are consistent with joint angle trajectories after capturing the behaviors. This calculation of consistent GRF profiles requires extra computation (Yamane & Nakamura, 2003), but we can easily and simultaneously measure the GRF profiles while capturing the joint angle trajectories. However, GRF is not directly observable from visual images, and it is difficult to always use a device to measure tri-axial GRF for the overall range of human movements. Also, the measurement of accurate acceleration to estimate GRF is rather difficult due to observation noise. Therefore, we represent primitives containing GRF using linear dynamical models and use SSSMs to recognize the appropriate primitives that correspond to the observed human behavior. Simultaneously, SSSMs are used to estimate joint angles, their velocity, and the GRFs from the noisy observation data. Estimated state variables are used to generate demonstrated movements with considering inverse statics of the robot model.

To evaluate our proposed method, we apply our imitation learning framework to 1) recognize human squatting motions and generate them with a four-link simulated robot model and to 2) recognize a combined squat–sway movement and generate them with a seven-link simulated robot model.

This paper is organized as follows. In Section 2, we present our imitation learning framework. We introduce the extraction method of primitives in Section 2.1 and the recognition method of primitives in Section 2.2. We describe how to generate imitated behaviors based on the recognized primitives in Section 2.3. In Section 3, we describe how we apply the proposed method to the simulated robot models. We also present the generalization performance of our framework on the four-link models with different physical parameters.

2. Imitation learning framework using movement primitives

Our learning system has three steps. We first construct a motion database that collects joint angles $\boldsymbol{\theta}$, joint angle velocities $\dot{\boldsymbol{\theta}}$, and GRF $\mathbf{f}_{\mathrm{grf}}$ from various humans behaviors by using a motion capture system and a set of force plates. Then, apply our imitation learning system to recognize newly observed human behaviors and generate the imitated movement using robots:

1. We extract primitives by learning the parameter of the linear dynamical models with using the constructed motion database (see Appendix A).
2. The extracted primitives are used in switching state-space models (SSSMs) to recognize newly observed motion sequences. Simultaneously, SSSMs estimate joint angles $\boldsymbol{\theta}^d$, joint angle velocities $\dot{\boldsymbol{\theta}}^d$, and the ground reaction force $\mathbf{f}_{\mathrm{grf}}$ (GRF) from the noisy observation of joint angles $\boldsymbol{\theta}^o$ and joint angle velocities $\dot{\boldsymbol{\theta}}^o$.
3. To generate imitated movements, first, the estimated GRF is scaled by the weight ratio between a demonstrator and a robot. Then, feedforward joint torques $\boldsymbol{\tau}_F$ to generate the scaled GRF $\mathbf{f}^d_{\mathrm{grf}}$ are derived. To track the estimated joint angles $\boldsymbol{\theta}^d$ and joint angle velocities $\dot{\boldsymbol{\theta}}^d$, we also use a proportional-derivative (PD) controller where the output of the controller is denoted as $\boldsymbol{\tau}_J$. The estimated joint angles $\boldsymbol{\theta}^d$ and joint angle velocities $\dot{\boldsymbol{\theta}}^d$ are used as the desired values for the PD controller.

Fig. 1 shows a schematic diagram of the proposed method.

In the following sections, we explain how we extract and recognize primitives and how we generate the imitated behaviors.

2.1. Extraction of primitives

We first extract primitives from captured human behaviors by using the Gaussian mixture of linear dynamical models (see Appendix A). We define the one linear dynamical model as one primitive. Then, a newly observed human behavior is recognized as a combination of these primitives by using switching state-space models (SSSMs) (Ghahramani & Hinton, 2000).

2.2. Recognition of primitives

We try to estimate the M continuous latent vectors $\mathbf{x}_t^m = \left[\boldsymbol{\theta}^{d\top}, \dot{\boldsymbol{\theta}}^{d\top}, \mathbf{f}_{\mathrm{grf}}^{\top}\right]^{\top}$ $(m = 1, \ldots, M)$, and the discrete latent state s_t from the observation $\mathbf{y}_t = \left[\boldsymbol{\theta}^{o\top}, \dot{\boldsymbol{\theta}}^{o\top}\right]^{\top}$ $(t = 1, \ldots, T)$. The discrete state s_t works as a switching variable to select a primitive which well represents an observed motion (see also Fig. 1). The joint probability of observations and the latent states can be factored as

$$P\left(s_{1,\ldots,T}, \mathbf{x}^{1,\ldots,M}_{1,\ldots,T}, \mathbf{y}_{1,\ldots,T}\right) = P(s_1)\prod_{t=1}^{T-1} P(s_{t+1}|s_t)\prod_{m=1}^{M} P(\mathbf{x}_1^m)\prod_{t=1}^{T-1} P \times (\mathbf{x}^m_{t+1}|\mathbf{x}^m_t)\prod_{t=1}^{T} P(\mathbf{y}_t|\mathbf{x}^1_t, \ldots, \mathbf{x}^M_t, s_t), \tag{1}$$

where $P(s_1)$ is the initial state probability of the discrete latent state, and $P(s_{t+1}|s_t)$ is the transition probability. The linear Gaussian dynamical model of each continuous latent vector, where the vector includes joint angles, joint angular velocities and GRF, can be represented as

$$P(\mathbf{x}^m_{t+1}|\mathbf{x}^m_t) = \mathcal{N}(\mathbf{x}^m_{t+1}|\mathbf{A}^m\mathbf{x}^m_t, \mathbf{Q}^m), \tag{2}$$

where $\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance $\boldsymbol{\Sigma}$. $\mathbf{A}^m$ represents the m-th linear dynamical model and