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Learning Stylistic Dynamic Movement Primitives from Multiple Demonstrations

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***Abstract*— In this paper, we propose a novel concept of movement primitives called *Stylistic Dynamic Movement Primitives (SDMPs)* for motor learning and control in humanoid robotics. In the SDMPs, a diversity of styles in human motion observed through multiple demonstrations can be compactly encoded in a movement primitive, and this allows style manipulation of motion sequences generated from the movement primitive by a control variable called a style parameter. Focusing on discrete movements, a model of the SDMPs is presented as an extension of Dynamic Movement Primitives (DMPs) proposed by Ijspeert et al. [1]. A novel learning procedure of the SDMPs from multiple demonstrations, including a diversity of motion styles, is also described. We present two practical applications of the SDMPs, i.e., stylistic table tennis swings and obstacle avoidance with an anthropomorphic manipulator.**

***Index Terms*— Stylistic Dynamic Movement Primitives, SDMPs, Imitation Learning, Human Motion Styles, Humanoid Robotics**

I. Introduction

In humanoid robots, motor learning and control remain among the most challenging tasks. Most difficulties are caused by the huge number of Degrees-of-Freedom (DoFs) associated with a large number of joints in humanoid robots, i.e., the curse of dimensionality. The learning from demonstration (or imitation learning, learning by watching) can be anticipated as one of the key frameworks for solving the curse based on the structural similarity between humans and humanoid robots [2]. In such a scenario, a human motion sequence is observed as a seed of a movement primitive for learning.

In the literature on computer graphics and animation of human motion, it has been recognized that a human motion sequence has motion-sequence-specific features called *style*. A diversity of motion styles can be observed among several individuals. Even for the same behavior by an individual, its motion sequences captured by a motion capture system have a certain variation. In other words, each motion sequence has a distinct choreography, i.e., style [3], [4], [5], [6], [7], [8].

The style is a vital component for human-like animation because it significantly affects not only quantitative difference in joint angle trajectories, but also its impressions

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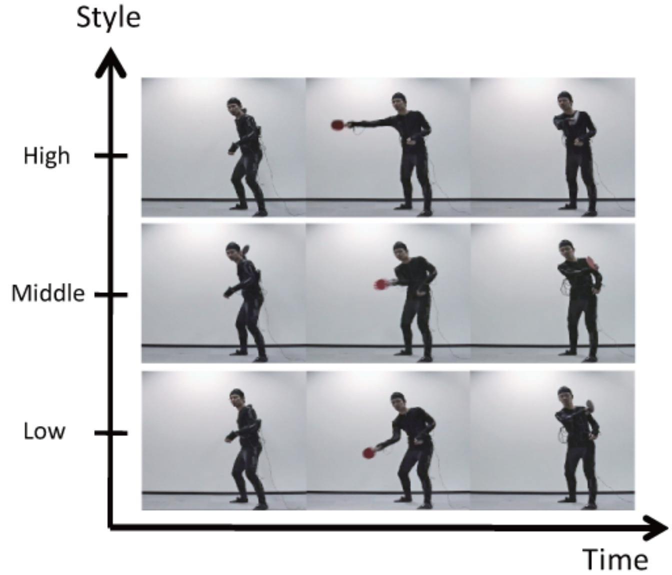


Fig. 1. Sequential snapshots of stylistic table tennis swing movements. The subject performs the same behavior (forehand) in many trials with different virtual balls as a target for a via-point. Such difference affects joint trajectories and resulting styles in each motion sequence while preserving its contents as a forehand movement.

on the audience. In general, in several human behaviors, much swinging of arms and legs could represent happiness (or anger) while less swinging might represent sadness (or calmness). Several techniques for the synthesis of human-like computer graphics and animations with various styles have been explored in [3], [9], [10], [4], [5], [6], [7], [8]. Most approaches commonly involve separating styles from the content of motion sequences, i.e., style content separation, inspired by a pioneering study by Tenenbaum et al. [11]. Since such approaches basically lead to a two-factor model that consists of independent control variables for style and content, it can be a useful tool for many applications of the character animation synthesis.

Meanwhile, in a more functional sense for motor control, the style of human motion can be interpreted as a result of encoding the environmental situations in the motion sequence. Two illustrative examples are taken up in this paper. The first example is a table tennis swing as illustrated in Fig. 1. The subject performs the same behavior in many trials (forehand swings with almost the same initial and goal postures), but imagines different positions of the virtual ball as a target for a via-point in the swing motion. Such difference largely affects joint trajectories and resulting styles

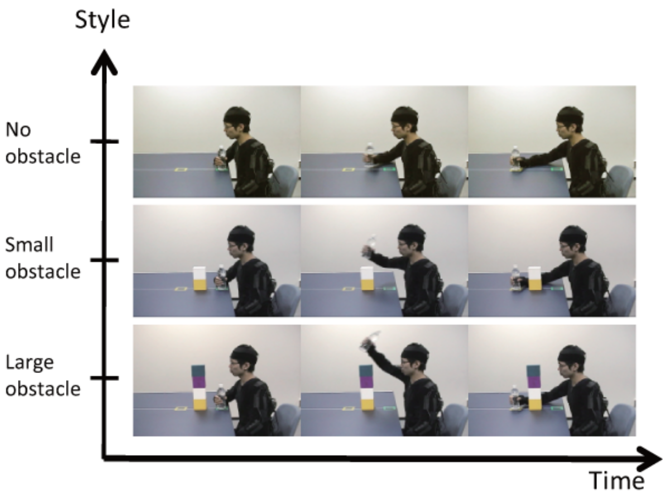
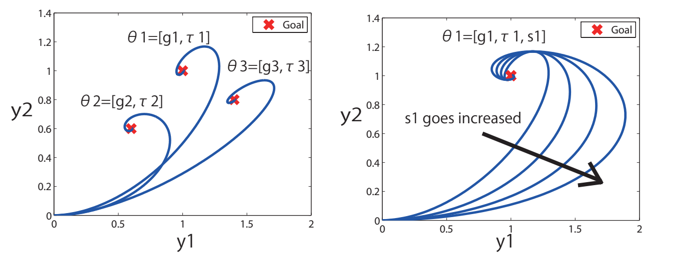


Fig. 2. Sequential snapshots of stylistic reaching movements. The subject performs the same content of motion (point-to-point reaching) with different obstacles to be avoided. Such difference largely affects joint trajectories and resulting styles in each motion sequence while preserving its content as a point-to-point movement.



(a) DMPs (b) SDMPs

Fig. 3. Trajectories of a discrete (reaching) movement generated by (a) Ordinal dynamic movement primitives and (b) Stylistic dynamic movement primitives. DMPs have two control variables, where g denotes the goal position and τ denotes the temporal scaling factor as illustrated in (a). SMDPs have an additional variable s called a style parameter as a control variable of style of movement. and the effect of the style parameter is illustrated in (b). The increase of $s1$ gradually changes the approach of the trajectory to the goal point, i.e., style of motion is manipulated.

in motion sequences. Another illustrative example is obstacle avoidance as depicted in Fig. 2. The subject performs the same behavior (point-to-point reaching with the same initial and goal states); however, different obstacles are put between the points. Different obstacles require the subject to use different avoidance trajectories according to their heights, and result in different styles in motion sequences. In these examples, motion styles have functional roles (hitting balls or avoiding obstacles) for solving tasks in the real environment. Therefore, the motion style is a significant factor not only for emotional graphics and animations, but also for motor control of humans and humanoids to solve several tasks in the real environment; however, not much attention has been paid to this so for.

In this paper, we propose a novel concept of movement primitives called *Stylistic Dynamic Movement Primitives (SDMPs)* for motor learning and control in humanoid robotics. In the SDMPs, a diversity of motion styles in human behavior observed by multiple demonstrations can be compactly encoded in a movement primitive, and this allows the style manipulation by a control variable called a style parameter in the generated motions. Focusing on discrete movements, a model of the SDMPs is presented as an extension of the DMPs proposed by Ijspeert et al. [1]. The SDMPs have a fascinating characteristic:

- Manipulability of motion style by a style parameter.

This scalability makes the applicability of the movement primitives much wider in real environmental tasks. Note also that all advantages of the DMPs compared with other motor primitive (human motion) models [12], [13], [14] are maintained in the SDMPs, i.e., asymptotic and global stability, robustness for disturbances and temporal and spatial scalability [1], [15]. With these features, the SDMPs are more suitable stylistic models for motor control in humanoid robotics than previously proposed stylistic models such as [3], [9], [10], [4], [5], [6], [7], [16], [8]. A motion library based approach, proposed by Gams et al. [17], could also allow to synthesize novel motion styles in DMP framework; however, it requires to execute the learning process for DMPs at every motion synthesis trial because the processes of motion synthesis and learning DMPs are separated. In our approach, once a SDMP is learned from multiple demonstrations, the synthesis of motion style can be achieved by a style parameter even in motion.

A novel learning procedure of the SDMPs from multiple demonstrations is also described. The concept of the learning procedure is to learn a parametric-attractor landscape in the movement primitive from multiple demonstrations, which is parametrized by the style parameter. We call this *stylistic attractor landscape*. Thus, we can manipulate the shape of attractor landscapes by the style parameter to become suitable for imitation of a specific (or novel) demonstration with a specific motion style. Figure 3 illustrates our SDMPs for discrete movements with a 2-DoFs motor system. In addition to the scalability of DMPs in goal position g and time constant τ as in Fig. 3 (a), we can smoothly manipulate the style (approach the goal) of the generated motions by changing the style parameter as shown in Fig. 3 (b).

In both cases of table tennis swing and obstacle avoidance, it is useful to model a set of motion sequences as a SDMP. By combining the SDMPs with a mapping between the style parameter and perceptual feedback of the ball position or obstacle's height, proper forehand skill and obstacle avoidance strategy in both a natural-looking and functional sense can be compactly achieved. This paper aims to develop a novel framework for learning such stylistic movement primitive models from multiple demonstrations rather than trying to solve specific tasks. Recent progresses in each task can be founded for table tennis in [18], [19], [20]. and for obstacle avoidance in [21], [22].

The organization of this paper is as follows. In section II, we first briefly introduce the DMPs and the learning procedure focusing on discrete movements along with the description in [1], [15]. We then propose a model of the SDMPs, and a novel learning procedure with an illustration through simple application. Section III describes the experimental settings and obtained results. We present two practical applications of the SDMPs, i.e., stylistic table tennis swings and obstacle avoidance with an anthropomorphic manipulator. Section IV concludes this paper.

II. LEARNING STYLISTIC ATTRACTOR LANDSCAPES

A. *Dynamic Movement Primitives* [1], [15]

We briefly explain the definition of DMPs focusing on discrete movements. Assume that we have a point attractive system as a control policy of one-DoF motor system described by the second order dynamics as:

$$\tau \dot{z} = \alpha_z \left(\beta_z \left(g - y \right) - z \right) \tag{1}$$

$$\tau \dot{y} = z + f \tag{2}$$

where g denotes a known goal position, α_z, β_z are time constants, τ is a temporal scaling factor. $y, \dot{y}$ correspond to the desired position and velocity generated by the policy [1]. For appropriate settings of parameters α_z, β_z with the constraint $f = 0$, these equations have a global stability with a unique point attractor g, i.e., y converges to g after a transient from any initial conditions.

In the DMPs, the above dynamics is applied for a learning from demonstration scenario by introducing an additional dynamical system of state x as

$$\tau \dot{x} \quad = \quad -\alpha_x x \tag{3}$$

and following nonlinear function f as

$$f(x) \quad = \quad \frac{\sum_{i=1}^{N} \Psi_i(x) w_i x}{\sum_{i=1}^{N} \Psi_i(x)}, \tag{4}$$

$$\Psi_i(x) \quad = \quad \exp\left(-h_i (x - c_i)\right) \tag{5}$$

where $\Psi_i(x)$ is a nonlinear kernel function, c_i and h_i are the center and bandwidth parameters. We call the system in eq(3) a *canonical system* as one of the most basic dynamic systems available to create a point attractor. With this, the nonlinear dynamical system in eqs(1) and (2) is called *output system*, and the system including both is called the Dynamic Movement Primitives (DMPs). If the initial condition of x is 1 and α_x is properly set for the system to be stable, $x(t) \in [0, 1]$ is considered as a phase variable for $f(x)$ because $\Psi_i(x)$ put on the point c_i is defined in the space of phase variable x, and x also acts as a gating term for $f(x)$. Assuming the boundness of the weight w_i, y asymptotically converges to the unique point g because the nonlinear function term f vanishes with the convergence of phase x to 0 through time evolution in the canonical system.

Learning parameter $\mathbf{w} = [w_1, \cdots, w_N]^T$ to form the attractor to become a landscape suitable for imitation of a given trajectory $\{y_{\text{demo}}(t_c)\}$, $t_c = c\Delta t$, $c = 1, \cdots, C$ with its duration $T = C\Delta t$ can be accomplished by a supervised learning algorithm. The target trajectory is given as $f_{\text{target}}(t_c) = \tau \dot{y}_{\text{demo}}(t_c) - z_{\text{demo}}(t_c)$ in eq(2), where $z_{\text{demo}}(t_c)$ is obtained by integrating eq(1) with $y_{\text{demo}}(t_c)$ instead of $y(t_c)$. Its input is corresponding phase value $x(t_c)$. We use a vector representation of each trajectory as $\mathbf{y}_{\text{demo}} = [y_{\text{demo}}(t_1), \cdots, y_{\text{demo}}(t_C)]^T$ for short. It is also applied for $\mathbf{f}_{\text{target}} = [f_{\text{target}}(t_1), \cdots, f_{\text{target}}(t_C)]^T$ and $\mathbf{x} = [x(t_1), \cdots, x(t_C)]^T$.

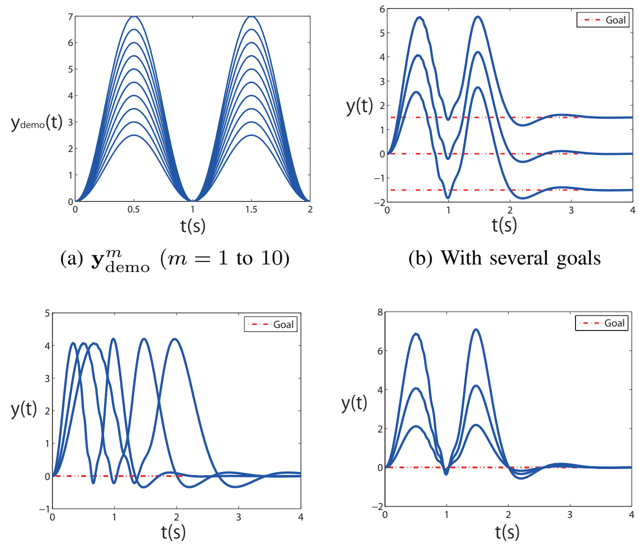
In the original study [1], Locally Weighted Learning (LWL) was applied for solving this, i.e., for determining the kernel functions Ψ_i and weight w_i for all i. The learned DMP has an attractor landscape to generate similar trajectories to the demonstration by time evolutions. Temporal scaling and modification of goal position can be achieved easily by manipulating g and τ.

Note that for a multi-DoFs motor system, the output system eq(1) and eq(2) must be set for every DoF independently. The canonical system can be shared across all DoFs if they are coordinated.

B. *Stylistic dynamic movement primitives (SDMPs)*

In the learned DMPs above, a motion trajectory given as a demonstration can be encoded. Since a human motion sequence implicitly has motion-sequence-specific features called style in motion, the DMPs can be interpreted as the style-fixed motor primitive, and they do not have any

[1]For simplicity, we insert the function f in eq(2) rather than in eq(1) so that imitation is focusing on positions and velocities as in [1].



(a) $\mathbf{y}^{m}_{\text{demo}}$ ($m = 1$ to 10)

(b) With several goals

(c) With several temporal scaling factors

(d) With several styles

Fig. 4. Illustrative example of SDMPs for a one-DoF motor system from multiple demonstrations. (a) Ten trajectories $y_{\text{demo}}(t)$ as multiple demonstrations. A SDMP is then learned from the multiple demonstrations. Since the difference between all motions is in the amplitude of the wave, the specific style of the motion can be considered as the specific value of amplitude. (b) Trajectories generated from the learned SDMP with several goals. (c) Trajectories generated from the learned SDMP with several temporal scaling factors. (d) Trajectories generated from the learned SDMP with several style parameters. The amplitude of the wave, i.e., style in motion is manipulated by the style parameter.

control variable of style. Also, it is impossible to learn motor primitives separately for all possible motion sequences with a diversity of motion styles. Our solution for avoiding such an explosion of the number of primitives is to redefine a motor primitive as a one-step higher level representation. If the DMPs have an another control variable that can manipulate the style of motion independently to other control variables as time scaling τ and goal position g, the range of applications would be significantly spread for various tasks in the real environment (two practical applications from among many possibilities are shown in this paper). This motivates us to propose a novel concept of movement primitives called stylistic dynamic movement primitives (SDMPs). The SDMPs have three independent control variables of time scaling τ, goal position g and style parameter $\mathbf{s} \in \mathbb{R}^J$. The style parameter $\mathbf{s}$ determines the style of motion sequence generated by the primitives through time evolution independently of the effect of other variables.

A model of SDMPs for a one-DoF motor system is proposed as follows:

$$\tau \dot{z} = \alpha_z \left(\beta_z (g - y) - z\right) \tag{6}$$

$$\tau \dot{y} = z + \tilde{f} \tag{7}$$

and

$$\tau \dot{x} = -\alpha_x x \tag{8}$$

$$\tilde{f}(x; \mathbf{s}) = \left(\sum_{j=1}^{J} \frac{\sum_{i=1}^{N} \Psi_{ji}(x) w_{ji} s_j}{\sum_{i=1}^{N} \Psi_{ji}(x)} \right) x \tag{9}$$

$$\Psi_{ji}(x) = \exp\left(-h_{ji}(x - c_{ji})\right) \tag{10}$$

where $\mathbf{W} = [\mathbf{w}_1, \cdots, \mathbf{w}_J]$ is parameter matrix, $\mathbf{s} = [s_1, \cdots, s_J]$ is style parameter, $\Psi_{ji}(x)$ is nonlinear kernel function, c_{ji} and h_{ji} are its center and bandwidth parameters, respectively. The SDMPs have the style parameter $\mathbf{s}$ additionally from the DMPs. The $\tilde{f}$ is a bilinear model of $\mathbf{W}$ and $\mathbf{s}$. Since the style parameter $\mathbf{s}$ only affects the nonlinear attractor dynamics through the term $\tilde{f}(x; \mathbf{s})$, it is obvious that the style parameter $\mathbf{s}$ controls the shape of attractor landscapes to represent a diversity of motion styles independently to time scaling τ and goal position g. Thus, $\tilde{f}(x; \mathbf{s})$ represents the stylistic-attractor landscapes. By fixing the value of $\mathbf{s}$, the style of the generated motion sequence is specified. Note that the global stability with a unique point g is preserved in the SDMPs as well as the DMPs if the we assume the boundness of the weight w_{ij} and s_j for all i and j.

C. Algorithm for learning stylistic-attractor landscapes

The learning of $\mathbf{W}$ in SDMPs can be accomplished with multiple demonstrations of the same behavior (e.g., forehand swing) including a diversity of motion styles. Focusing on one-DoF motor system again, we propose a novel learning procedure with the following four steps:

(i) Alignment of demonstrations as a preprocessing for next steps. Assume that we have M sets of trajectories as multiple demonstrations $\{y^m_{\text{demo}}(t^m_c)\}$, $m = 1, \cdots, M$, $t^m_c = c\Delta t$, $c = 1, \cdots, C^m$, where the duration of each demonstration is given as $T^m = C^m \Delta t$. After selecting a nominal trajectory indexed by $n \in \{1, \cdots, M\}$, other trajectories are time-scaled by the ratio $\frac{T^n}{T^m}$ so that all trajectories can be represent as the same size of vector as $\mathbf{y}^m_{\text{demo}} \in \mathbb{R}^{C^n \times 1}$ for all m.

(ii) Calculation of target $\mathbf{f}^m_{\text{target}}$ for each demonstration $\mathbf{y}^m_{\text{demo}}$ separately along with the same process used in the DMPs as presented in the previous subsection. By applying this process for all demonstrations $\{\mathbf{y}^1_{\text{demo}}, \cdots, \mathbf{y}^M_{\text{demo}}\}$, we obtain $\{\mathbf{f}^1_{\text{target}}, \cdots, \mathbf{f}^M_{\text{target}}\}$.

(iii) Extraction of *basis targets* $\{\mathbf{f}^1_{\text{basis}}, \cdots, \mathbf{f}^J_{\text{basis}}\}$ from targets $\{\mathbf{f}^1_{\text{target}}, \cdots, \mathbf{f}^M_{\text{target}}\}$ so that any target $\mathbf{f}^m_{\text{target}}$ is approximately represented as $\mathbf{f}^m_{\text{target}} = \sum_{j=1}^{J} s^j \mathbf{f}^j_{\text{basis}}$, where typically $J \ll M$. The basis targets can be extracted by a matrix factorization with Singular Value Decomposition (SVD). Let $\mathbf{F}^{\text{all}}_{\text{target}} = [\mathbf{f}^1_{\text{target}}, \cdots, \mathbf{f}^M_{\text{target}}]^T$ be an $M \times C$ matrix. Then, SVD for this matrix leads to the following factorial representation as

$$\mathbf{F}^{\text{all}}_{\text{target}} = \mathbf{U}\Sigma\mathbf{V}^T \approx \mathbf{S}\mathbf{F}_{\text{basis}}. \tag{11}$$

We define the style parameter matrix $\mathbf{S} = [\mathbf{s}^1 \cdots \mathbf{s}^M]^T \in \mathbb{R}^{M \times J}$ to be the first $J (\leq M)$ rows of $\mathbf{U}$, and the basis target matrix $\mathbf{F}_{\text{basis}} = [\mathbf{f}^1_{\text{basis}} \cdots \mathbf{f}^J_{\text{basis}}]^T \in \mathbb{R}^{J \times C}$ to be the first J columns of $\Sigma\mathbf{V}^T$. The dimension J can be determined with the singular value spectrum.

(iv) Learning $\mathbf{W}$ is achieved by supervised learning with $\mathbf{f}^j_{\text{basis}}$ and corresponding phase vector $\mathbf{x}$ separately for each $j \in \{1, \cdots, J\}$ as

$$\mathbf{w}^*_j \leftarrow \arg\min_{\mathbf{w}_j} \sum_{c=1}^{C^n} \left(f^j_{\text{basis}}(t_c) - \frac{\sum_{i=1}^{N} \Psi_{ji}(x(t_c)) w_{ji}}{\sum_{i=1}^{N} \Psi_{ji}(x(t_c))} x(t_c) \right). \tag{12}$$

The optimal parameter $\mathbf{w}^*_j$ with a proper supervised learning algorithm leads to a stylistic-attractor landscape parametrized by style parameter $\mathbf{s}$ as $\tilde{f}(x; \mathbf{s})$ to form the SDMPs.

The interpretation of learning $\tilde{f}$ is that each attractor landscape to a target trajectory is identified by style parameter $\mathbf{s}$ spanned by $\{\mathbf{f}^1_{\text{basis}}, \cdots, \mathbf{f}^J_{\text{basis}}\}$. Typically $J \ll M$ if target trajectories are correlated, i.e., even with the increase of the number of demonstrations M, the dimension of style parameter J could be relatively small. This property leads to a compact representation of the SDMPs from multiple demonstrations. While the supervised learning problem in (iv) is often solved by standard least-square techniques such as LWL, in this paper, we utilize the Gaussian process regression [23] for the algorithmic simplicity and generalization performance.

D. Application to synthetic data for one-DoF system

Before application to complex motor systems, we experimentally illustrate the proposed technique for a discrete movement of a one-DoF motor system. As multiple demonstrations with different styles for motion sequences, we sampled ten trajectories $y^m_{\text{demo}}(t) = (1 + 0.25m)\sin(2\pi t - \pi/2) + (1 + 0.25m)$ for $m = 1$ to 10. Each trajectory was observed for 0.0 to 2.0sec, where initial state was $y(0) = 0.0$ and goal position was $g = 0.0$. Since the difference among all motions is in the amplitude of the wave, the specific style of the motion can be considered as the specific value of amplitude.

Figure 4(a) shows multiple demonstrations for imitation. Temporal scaling factor τ was determined so that x was less than 0.05 when the output was terminated as suggested by [1]. Time constant parameters were determined as $\alpha_z = 1.5$, $\beta_z = 1.5$ and $\alpha_x = 0.2$. Along with the steps in the learning procedure of SDMPs from multiple demonstrations as described in the previous subsection, $\mathbf{F}^{all}_{\text{target}}$ was successfully prepared. According to the spectrum of singular values of $\mathbf{F}^{all}_{\text{target}}$ through SVD, one basis target as $\mathbf{f}^1_{\text{basis}}$ was extracted and the corresponding style parameter matrix $\mathbf{S}$ was also estimated. Note that, in this case, a SDMP representing ten stylistic demonstrations was obtained as a significantly compact form.

Examples of time evolution of the SDMPs for motion generations are illustrated in Fig. 4(b)-(d). The time evolution of y represented the features of the demonstration very well (a bimodal shape), and it converged to the goal position $g = 0.0$ with a transient. As with the DMPs, both the goal position and temporal scaling of the time evolution were independently controlled by changing g and τ as shown in (b) and (c). The style of the trajectory was controlled by s as shown in (d) where the amplitude (style) of the trajectory was changed while time scaling and goal position were fixed.

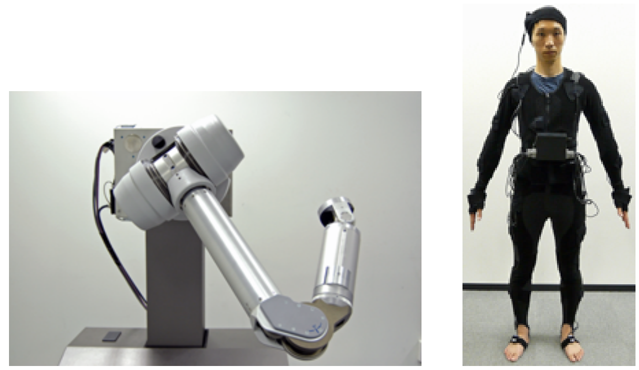
The feasibility and usefulness of the SDMPs is further investigated with an anthropomorphic manipulator through two practical applications, i.e., stylistic table tennis swings and obstacle avoidance.

III. Experiments

In this section, we present results for two practical applications of the SDMPs, i.e., stylistic table tennis swings and point-to-point reaching with obstacle avoidance for implementing on an anthropomorphic manipulator.

A. Stylistic Table Tennis Swings

In this experiment, stylistic table tennis swings are learned as a SDMP from multiple demonstrations, and it is implemented on and demonstrated by an anthropomorphic manipulator in Fig. 5(a). As shown in Fig. 1, the subject performed the forehand swings roughly from the same initial postures to goal postures. In each motion, the subject imagined different virtual balls as a target for a via-point. Such difference affects joint trajectories and resulting styles for motion sequences while preserving its contents as a forehand movement. Fifteen motion sequences were observed by a



(a) Manipulator (b) Motion capture

Fig. 5. Experimental instruments. (a) Anthropomorphic manipulator. (b) Gyro-type motion capture system.

gyro-type motion capture system as in Fig. 5(b). In order to adapt human's joint trajectories to the manipulator, the joint trajectories in the right arm of a human were translated in the manipulator's four-DoFs joint space (three for the shoulder, one for the elbow) through the inverse kinematics technique. The objective function of the inverse kinematics was coordinated by the position and orientations of end-effector and elbow. The obtained trajectories were set as $\mathbf{y}^m_{\text{demo}}(m \in \{1, \cdots, 15\})$ for the learning procedure of the SDMPs.

As a result of the SVD in the learning procedure (ii), we extracted three basis targets and fifteen style parameters each of which represents the style of each demonstration. For learning the SDMP from extracted basis targets, parameters were set as $J = 3$, $\alpha_z = 1.5$, $\beta_z = 1.5$ and $\alpha_x = 1.0$, $\tau = 0.03$ and $\mathbf{g} = [2.83, 1.51, -3.57, 0.03]$, respectively.

The learned SDMP was successfully implemented on the manipulator. The demonstrations of the forehand skill on the manipulator with different style parameters are presented in Fig. 6. The style parameter was set from $\mathbf{S}$ by selecting one column for each case, i.e., $\mathbf{s} = [-0.24, 0.43, 0.38]^T$ (top), $[-0.20, 0.15, 0.31]^T$ (middle) and $[-0.12, -0.16, -0.15]^T$ (bottom), respectively. All demonstrated swings were the forehand swing in table tennis with the same initial posture and goal position, but styles (trajectories to the goal) were largely different from each other to hit different positions of the ball suspended by a string during the swing as presented in Fig. 6.

By changing the style parameter $\mathbf{s}$ arbitrarily, we could synthesize a novel style of forehand swing. The duration of motion and goal position are also changed by manipulating τ and g as with DMPs.

B. Obstacle Avoidance

In this experiment, a motor skill of point-to-point reaching movements with an obstacle avoidance strategy is learned as a SDMP from multiple demonstrations, and it is implemented on and demonstrated by an anthropomorphic manipulator as shown in Fig. 5(a) as the swings in the previous subsection.

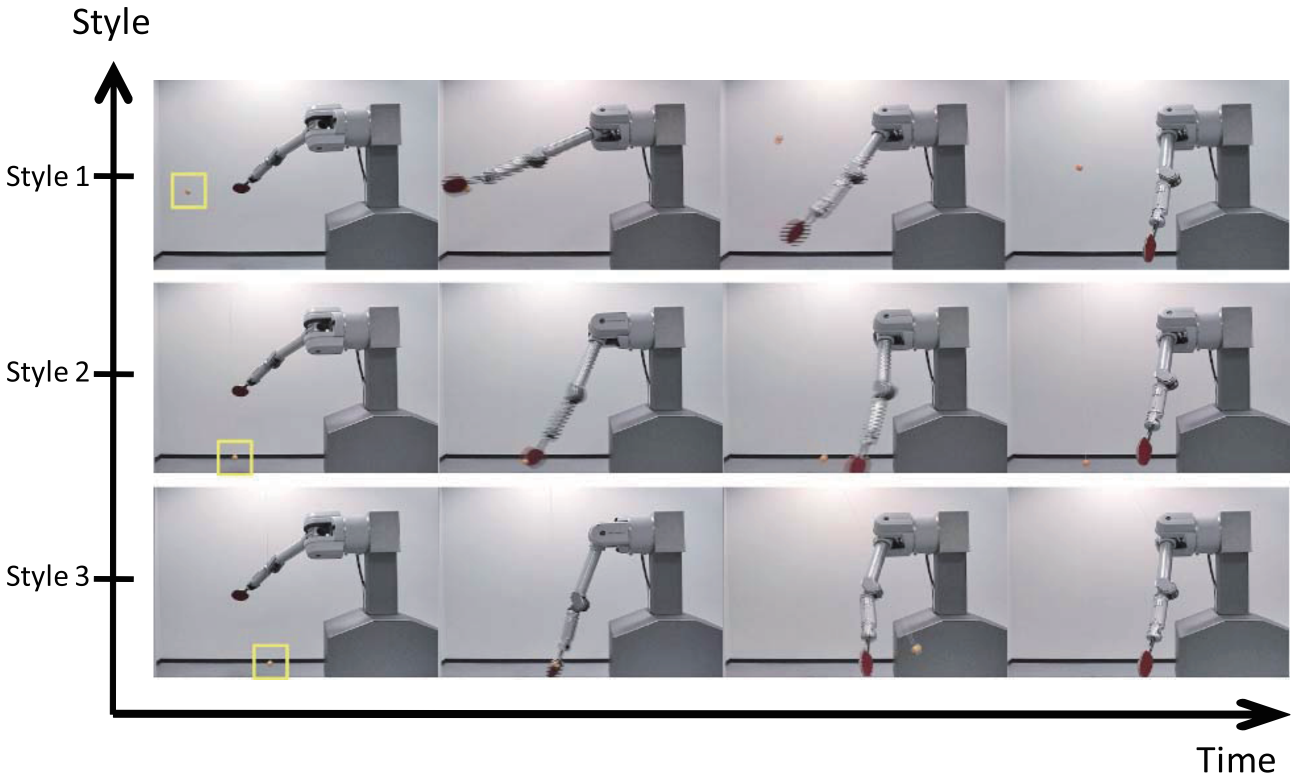


Fig. 6. Sequential snapshots of stylistic table tennis swings on an anthropomorphic manipulator. With the setting $\mathbf{g} = [2.83, 1.51, -3.57, 0.03]^T$ and $\tau = 1.2$, the style parameters were set as $\mathbf{s} = [-0.24, 0.43, 0.38]^T$ (top), $[-0.20, 0.15, 0.31]^T$ (middle) and $[-0.12, -0.16, -0.15]^T$ (bottom). All swings are the forehand swing in table tennis with the same initial posture and goal position, but, styles (trajectories to the goal) are largely different. Balls in different positions indicated by the box were successfully hit with properly selected style parameters by hand. Note that the ball was suspended by a string. The velocities of motions were set to be slower than actual strokes by human players because the focus of this experiment was in the synthesis of motion styles in forehand swing.

As shown in Fig. 2, the subject performed the point-to-point reaching with different heights of the obstacle to avoid them from over. Such difference largely affects joint trajectories and resulting styles for motion sequences while preserving its contents as the point-to-point reaching.

Fifteen motion sequences were observed by the motion capture system. The trajectories of a human right arm joint space were translated to the manipulator's four DoFs joint space, and they were set as $\mathbf{y}^m_{\mathrm{demo}}(m \in \{1, \cdots, 15\})$ for the learning procedure of the SDMPs.

As a result of the SVD, we extracted three basis targets and fifteen style parameters each of which represents the style of each demonstration. For learning the SDMP from extracted basis targets, parameters were set as $J = 3$, $\alpha_z = 1.5$, $\beta_z = 1.5$, $\alpha_x = 0.5$ and $\tau = 0.3$, respectively. The goal for each joint were as $\mathbf{g} = [-0.55, -0.97, 0.54, -1.42]$.

The learned SDMP was successfully implemented on the anthropomorphic manipulator as well as the swing case. The demonstrations of the reaching on the manipulator with different style parameters are presented in Fig. 7. The style parameter was set from $\mathbf{S}$ by selecting one column for each obstacle, i.e., $\mathbf{s} = [-0.06, -0.12, -0.38]^T$ (top), $[0.12, -0.28, 0.00]^T$ (middle) and $[0.27, -0.23, 0.50]^T$ (bottom), respectively. Each style parameter corresponded to an obstacle avoidance strategy for a specific height of the obstacle. In the experiment, several obstacles were successfully avoided with properly set style parameters by hand as presented in Fig. 7.

IV. Discussion

In this paper, we proposed a novel concept of movement primitives called Stylistic Dynamic Movement Primitives (SDMPs) for motor learning and control in humanoid robotics. In the SDMPs, a diversity of styles in human behavior observed through multiple demonstrations can be compactly encoded in a movement primitive, and it allows the style manipulation of motion sequences generated from the movement primitive by a control variable called a style parameter. Focusing on discrete movements, a model of the SDMPs was presented as an extension of the Dynamic Movement Primitives (DMPs) proposed by Ijspeert et al. [1]. A novel learning procedure of the SDMPs from multiple demonstrations including a diversity of motion styles was also described. We presented two illustrative applications of the SDMPs among various possibilities, i.e., stylistic table tennis swings and obstacle avoidance with an anthropomorphic manipulator.

By combining the SDMPs with a mapping between the style parameter and perceptual feedback of the ball position

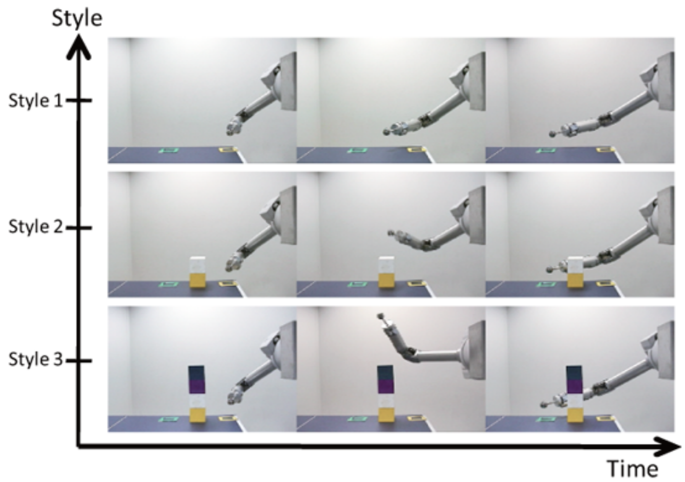


Fig. 7. Sequential snapshots of point-to-point reaching with obstacle avoidance strategy on an anthropomorphic manipulator. With the setting $\mathbf{g} = [-0.55, -0.97, 0.54, -1.42]^T$ and $\tau = 0.6$, the style parameters were set as $\mathbf{s} = [-0.06, -0.12, -0.38]^T$ (top), $[0.12, -0.28, 0.00]^T$ (middle) and $[0.27, -0.23, 0.50]^T$ (bottom). All motions are the reaching movement with the same initial posture and goal position, but, styles (trajectories to the goal) are largely different. In the experiment, several obstacles were successfully avoided by properly selecting style parameters.

or obstacle's height, proper forehand skill and obstacle avoidance strategy in both a natural-looking and functional sense could be compactly achieved, which would be addressed as a part of our future work.

While the SDMPs presented in this paper are based on the DMPs as in [1], it is easily combined with recently developed several extensions and modifications as in [21], [22]. With a different motivation, some studies have explored generalizations of the DMPs as in [24], [17]; however, compact representations of movement primitives are not obtained, unlike the SDMPs.

Our future work also includes extending the SDMP to rhythmic movements. Another work would be to apply it to a human-size whole body humanoid robot [25] for complex motor learning and control with several styles. For the purpose, several concerns such as joint limits and self collision should be managed in our approach.

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