Goal-directed Imitation with Self-adjusting Adaptor Based on a Neural Oscillator Network

Woosung Yang and Nak Young Chong, *Member*, *IEEE*

Abstract— **An innovative framework of imitation between dissimilar bodies is proposed to automatically achieve the goal of the perceived behavior. Biologically inspired control based on central pattern generators currently gains increasing attention to embody human-like rhythmic motions to humanoid robots. However, this control approach suffers from highly nonlinear dynamics of neural systems, difficulty of motion pattern generation, uncertainty of behavior between neural systems and biomechanics, and so on. To cope with these problems, the imitation technique is employed in this work. We first propose the self-adjusting adaptor to easily generate an appropriate motion pattern by modifying the perceived motion toward attaining the goal of the behavior. Secondly, we verify the property of entrainment of neural oscillator network in the proposed adaptor to duplicate the regenerated motion pattern. In the numerical simulations of biped locomotion, the perceived pattern data is regenerated to keep the direction of the foot contact force identical between the demonstrator and the imitator. Also, the neural oscillator is entrained by external signals under stable conditions. To the best of the authors' knowledge, this paper is the first work to validate the advantages of neural oscillator networks as a tool of imitation.**

Index Terms—**Humanoid Robot, Biped locomotion, Imitation learning, Self-adjusting adaptor, Neural oscillator**

I. Introduction

ALTHOUGH recent progress in robotics has yielded many humanoid robots, they are still very difficult to control. This is mainly because that the motion planning strategy which helps generate various behaviors is so far undetermined in dynamic environments. Behavior can be learned through reinforcement or imitation [1]. Reinforcement learning allows a robot to improve its behavior based on trial-and-error feedback. In contrast, imitation learning lets the designer specify entire behaviors by demonstration instead of using low level programming or trial-end-error by the robot. Thus, as the effective and powerful form of learning, imitation gains increasing attention and addresses primarily the following three challenges: 'what to imitate', 'how to imitate' and 'when to imitate' [2]. What to imitate refers to the problem of determining which of the features of the demonstration are relevant for the achievement of the task [3], [4]. 'How to imitate' is how to recognize and encode human in a way that makes it easily transferable to a robot [5]. This work focuses on the issue of how-to-imitate with particular emphasis on the dissimilar kinematics and dynamics between the demonstrator and the imitator and proposes a new framework to reproduce the goal of the imitated behavior.

Many researchers have studied and developed recognition tools for imitation [6]-[8]. Especially, Samejima *et al.* suggested a framework MOSAIC, where plural dynamics and inverse dynamics are implemented to predict and control motions [9], [10]. Also Inamura *et al.* [6] devised the mimesis model based on HMM which can imitate the motion of others and abstract the time-series motion patterns as symbol representation. Our new framework leads to a completely different approach that permits a robot to acquire optimal behaviors adapted to its body from the perceived demonstration. For this, we propose a tool for adaptation process, called self-adjusting adaptor, to facilitate imitation mapping between dissimilar bodies. What we intend to achieve in the proposed adaptor are: (1) how to easily generate a desired trajectory of the imitator, (2) how to keep the imitator robust against disturbances and changes in a complex environment, (3) how to make the imitator's behavior appropriate to accomplish its intended goal considering its kinematics and dynamics.

Humanoid robots may not be deployed in a wide variety of application without having a real-time programming tool. The application of imitation to humanoid robot programming has not been formalized yet. Therefore, this paper deals with how to generate the behavior of the robot appropriate for its intrinsic mechanism more easily and naturally. Within the proposed framework for automatic generation of robot behavior, (a) robots can learn and acquire any new motions from humans (and/or other robots) fast and easily, (b) similar motions can be adapted to the robot if both the demonstrator and the imitator have similar kinematics, (c) the imitator can find optimal motions through learning and repeated pattern recognition, (d) there is no need for analysis of nonlinear robot dynamics. Then, finally, humanoid robots may be able to behave autonomously using external motion patterns acquired by the vision sensor or downloading nominal data from its knowledge base. As a first step toward formalizing imitation learning, we address biped locomotion learning by imitation and present numerical simulations to verify the validities of the proposed framework.

The authors are with the School of Information Science, Japan Advanced Institute of Science and Technology, 1-1 Asahidai, Nomi, Ishikawa 923-1292, Japan (e-mail: woo-yang@jaist.ac.jp, nakyoung@jaist.ac.jp).

II. Behavior Imitation Between Dissimilar Bodies

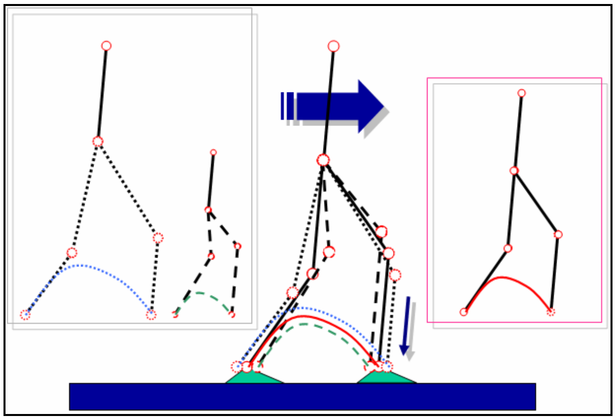

Fig. 1 Keeping the force direction identical in goal-directed imitation

Imitation can be classified into several different levels [2]. In the action-level imitation, the imitator carries out exactly the same actions as demonstration. In the program-level imitation, the imitator carries out an identical program which often has a hierarchical system invoking a sequence of subroutines. Thus, duplicated actions or programs carried out in inappropriate context fail to achieve desired goals. This requires the so-called effect-level imitation similar to the functional imitation introduced in [12]. Practically, the application of action- or program-level imitation to humanoid robots induces sophisticated problems in their stability and performance due to the different kinematics and dynamics of the demonstrator. Thus, we propose a novel method of the program-level imitation which can realize the features of effect-level imitation as well.

To simplify the analysis, hereafter we assume that there are similarities in kinematic configurations between the demonstrator and the imitator. However, the motion trajectory of the imitator should be regenerated adequately by considering the dissimilarities between their dynamic parameters and length ratios of the multi-segmented body parts. Also, the most notable observation in this work to produce the same effect of behavior is that the direction of the applied force at the point of action should be coincident between two bodies. Without this, any imitation method may not give exactly the same effect of behavior. Fig. 1 illustrates an example of this effect-level imitation of biped locomotion, where the direction of the applied force of the imitator at the ground contact point should be coincident with the demonstrator.

In this example, if any difference of the distance exists between the center of mass of the whole body and the point of the action of the force, every joint movement of the imitator is not exactly the same as those of the demonstrator. Under this condition, the direction that the imitator robot is applying the force to the ground, which should be coincident with that of the demonstrator, ensures that the action of the imitator is similarly duplicated as closely as possible. Here, we assume that the locomotion of the demonstrator is stable and the location of center of mass of the imitator changes along the vertical direction to maintain its locomotion stability. Also, because the imitator can recognize the difference between the original trajectory and the regenerated trajectory, the imitator can generate compensated behaviors accordingly to achieve the intended goal of the demonstrated motion. Likewise, although there are some problems which have not been considered yet, the regenerated motion trajectory will help the imitator achieve the goal-directed imitation, that is, the effect-level imitation.

III. Self-Adjusting Adaptor for Pattern Modification

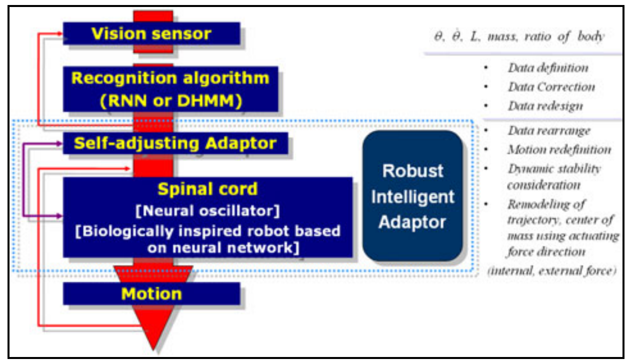

Fig. 2 Framework of motion imitation through self-adjusting adaptor

What is focused on in this section is how to imitate the external functional movement and behavior in the imitator's intrinsic mechanism. Technically, we develop the self-adjusting pattern adaptor through which the external motion pattern acquired by the vision sensor is regenerated into an appropriate data. This data enters the neural adaptor, where some input parameters are controlled autonomously to duplicate this data. The oscillator in the neural adaptor can be entrained with the input signal under the stable oscillation condition. Through this sequence illustrated in Fig. 2, the regenerated motion data is mapped into the imitator's motion space.

To imitate a behavior subject to dynamic constraints, it is required to predefine the parameters of the imitator such as the mass distribution within the body segments (which is known as in the form of body segment parameters), the link length ratio, the allowable output torque of the joint actuators, and so on. Especially, in the case of imitation between a human and a robot, these problems become more complicated. In human locomotion if the total distance of the hip to travel is 100%, the distance of the hip to travel during the single support phase is 85% and that of the distance during the double support phase is 15%. But in robot locomotion, the distance of the hip to travel during the single support phase is about 35% primarily because of the power limitation of joint actuators [13]. Thus, we have to consider the typical mass distribution within the body segments for dynamic stability and limitations of the actuator torque of the imitator for realization of dynamic motion. A uniform mass distribution is assumed in Fig. 3 which illustrates a trajectory of biped locomotion of the demonstrator for goal-directed imitation in our simulation. From the model in Fig. 3, considering the distance between the center of mass and the point of action of the contact force, the imitator can find its joint angle trajectories to keep the applying force direction identical given by

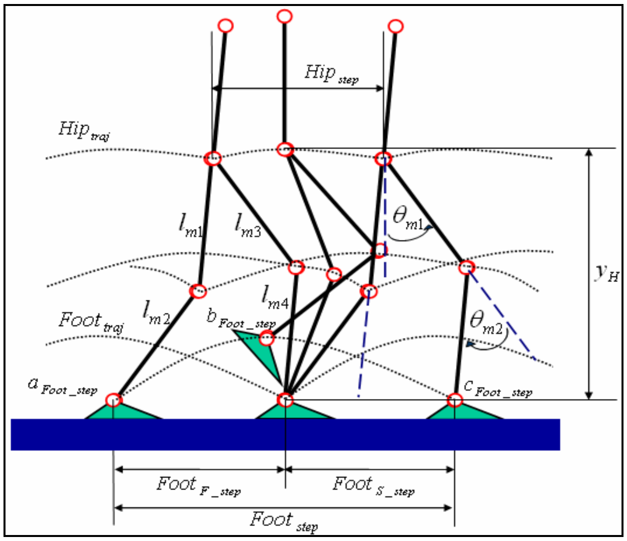

Fig. 3 Trajectory pattern for the locomotion of bipedal robot

$$\theta_{R1,3} = \cos^{-1}\left\{\frac{(l_R l_{m1,3}/(l_{m1,3}+l_{m2,4}))\cos\theta_{m1,3}}{l_{R1,3}} + \frac{((l_R l_{2,4}/(l_{m1,3}+l_{m2,4}))-l_{R2})\cos(\theta_{m1,3}+\theta_{m2,4}))}{l_{R1,3}}\right\} \quad (1)$$

$$\theta_{R2,4} = (\theta_{m1,3}+\theta_{m2,4}) - \theta_{R1,3}$$

where θ_R, l_R, m_R are the joint angel, length, and mass of the imitator, and θ_m, l_m, m_m are the joint angel, length, and mass of the demonstrator, respectively. In this example, $\theta_{m1,3}+\theta_{m2,4}$ means the direction that the demonstrator applies the force to the ground.

IV. Simulation Results for Locomotion Trajectory Adaptation

We performed numerical simulations of the proposed imitation method using the self-adjusting adaptor for the program-level imitation toward attaining goal-directed imitation. The imitator robot is assumed to have the same size as the humanoid robot HOAP-II developed by Fujitsu, and the two different demonstrators are considered. It can be verified from Figs. 4, 6, 8 and 10 that the trajectory generated by the self-adjusting adaptor is more stable and close to the demonstrator's trajectory for both of the two demonstrators. Especially, if the length ratio of the demonstrator thigh is longer than that of the imitator, or the length ratio of the demonstrator shank is shorter than that of the imitator, the kinematic constraint violates as shown in Fig. 9. Because of this, in the regenerated data by the self-adjusting adaptor, the trajectory of the foot distance of the imitator is longer than that of the demonstrator in Case I, and Case II reveals the opposite result. Moreover, the trajectories of the center of mass of the demonstrators and the imitator in Figs. 7 and 11 show that the regenerated data through the adaptor is valid and usable from the viewpoint of the body dynamics. Finally applying this algorithm to our humanoid robots, we execute the simulations in a 3-D environment on the humanoid robot software platform, OpenHRP [20]. Fig. 12 shows the joint angle trajectories of the demonstrator robot computed using the inverse kinematics if the perceived foot and hip trajectories are given. Fig. 13 shows the regenerated data for the imitator robot acquired by the proposed self-adjusting adaptor. The simulation verifies one of the critical conditions needed to yield the goal-attained imitation with dynamic stability.

A. Case I: The whole length and the mass of the demonstrator are greater than those of the imitator

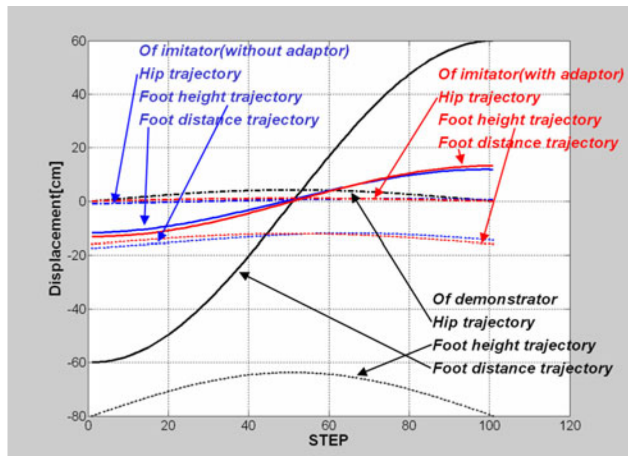

Fig. 4 Trajectories of the height of the hip and foot and the foot distance of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 40cm, 60cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

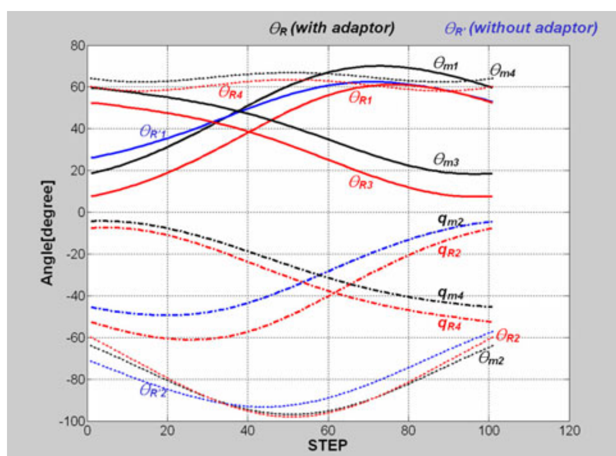

Fig. 5 Trajectories of joint angles of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 40cm, 60cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

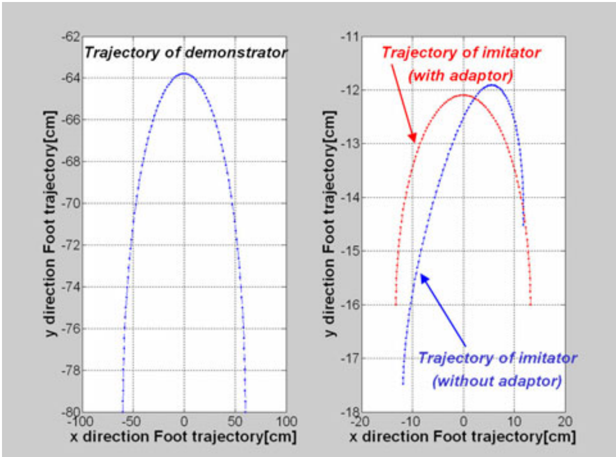

Fig. 6 Trajectories of the demonstrator and the imitator with/without adaptor in x-y plane: $l_{m1,3}$, $l_{m2,4}$ = 40cm, 60cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

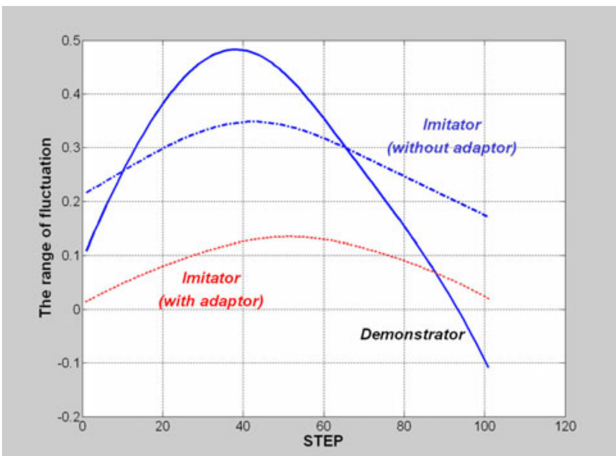

Fig. 7 Trajectories of the center of mass of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 40cm, 60cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

B. Case II: The whole length and the mass of the demonstrator are less than those of the imitator

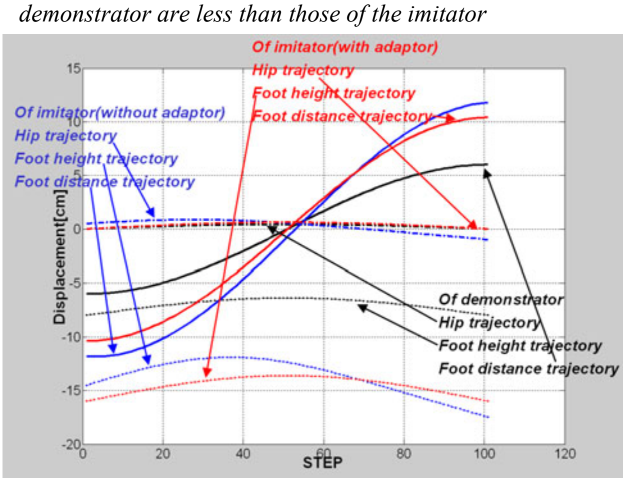

Fig. 8 Trajectories of the height of the hip and foot and the foot distance of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 6cm, 4cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

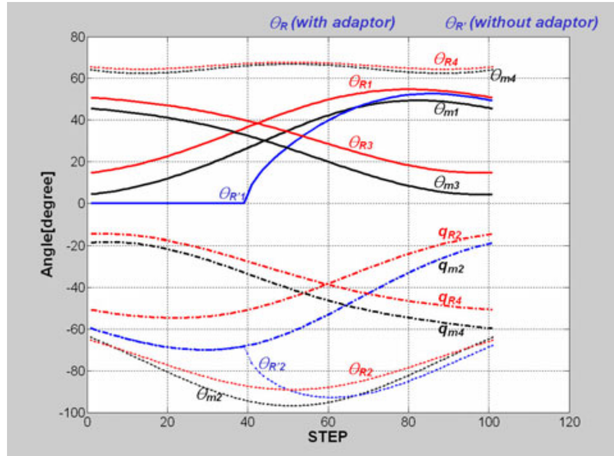

Fig. 9 Trajectories of joint angles of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 6cm, 4cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

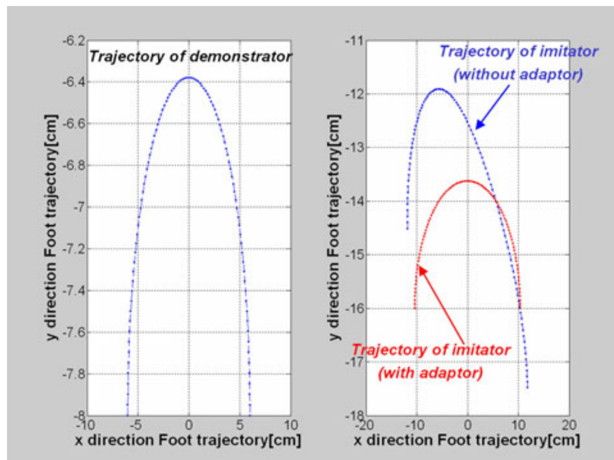

Fig. 10 Trajectories of the demonstrator and the imitator with/without adaptor in x-y plane: $l_{m1,3}$, $l_{m2,4}$ = 6cm, 4cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10츠

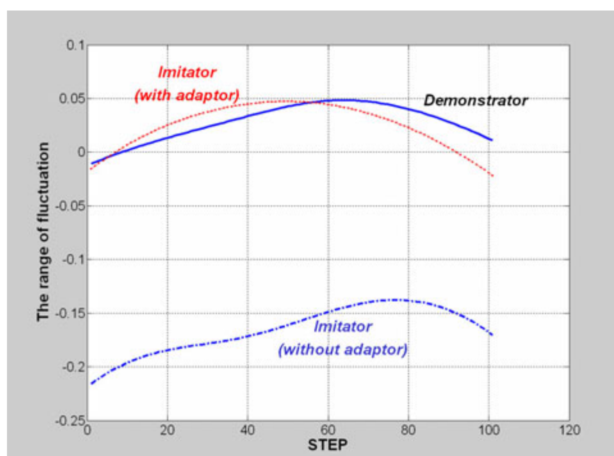

Fig. 11 Trajectories of the center of mass of the demonstrator and the imitator with/without adaptor: $l_{m1,3}$, $l_{m2,4}$ = 6cm, 4cm; $l_{R1,3}$, $l_{R2,4}$ = 10cm, 10cm

C. Regeneration of humanoid locomotion patterns

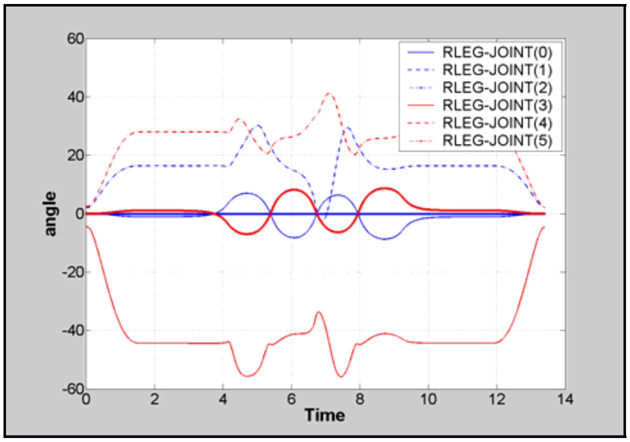

Fig. 12 Trajectories of joint angles of the demonstrator: $l_{m1,3}$, $l_{m2,4}$ = 33.25cm, 30cm

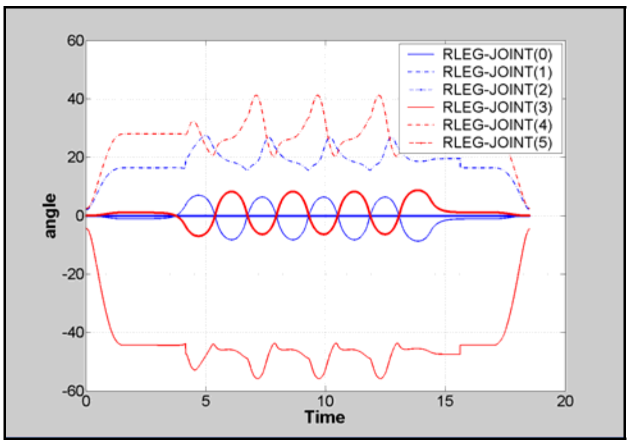

Fig. 13 Trajectories of joint angles of the imitator: $l_{R1,3}$, $l_{R2,4}$ = 43.25cm, 20cm

V. Application of Neural Oscillator to Self-Adjusting Adaptor

We employ CPGs with neural oscillators which generate rhythmic signals as self-adjusting adaptor for imitation. Neural oscillators are entrained with external stimuli at a sustained frequency. Thus, basically, neural oscillators have been applied to CPGs of biologically inspired control architectures for humanoid robots with rhythmic motions. Also, neural oscillators show stability against perturbations through global entrainment among the neural and musculo-skeletal systems and the environment [14]. Specifically, a neural oscillator for biped locomotion was studied theoretically [15], and was applied to a humanoid robot as CPG with reinforcement learning [16]. To the best of the authors' knowledge, it is the first time to exploit the property of entrainment of the neural oscillator to arbitrarily modified input signals.

A. Neural oscillator

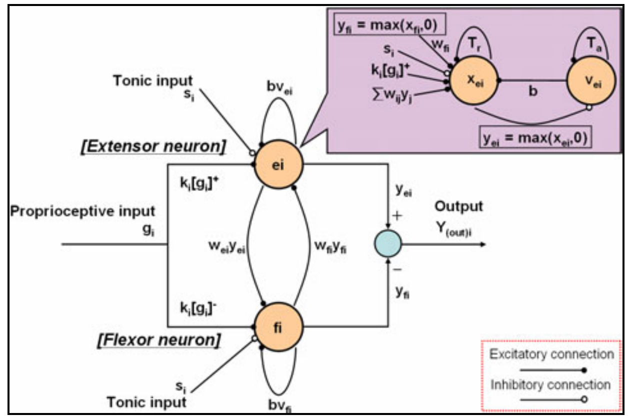

Fig. 14 Schematic of neural oscillator

The oscillator model consists of two simulated neurons arranged in mutual inhibition as shown in Fig. 14 [17], [18]. If gains are properly tuned, the system exhibits limit cycle behavior. The appearance of a stable limit cycle can be derived analytically and describes the firing rate of a real biological neuron with self-inhibition. A neural oscillator is represented by a set of nonlinear coupled differential equations as

$$
\begin{aligned}
T_r\dot{x}_{ei}+x_{ei} &= -w_{fi}y_{fi}-\sum_{j=1}^{n}w_{ij}y_j-bv_{ei}-\sum k_i[g_i]^+ +s_i\\
T_a\dot{v}_{ei}+v_{ei} &= y_{ei}\\
y_{ei} = [x_{ei}]^+ &= \max(x_{ei},\ 0)\\
T_r\dot{x}_{fi}+x_{fi} &= -w_{ei}y_{ei}-\sum_{j=1}^{n}w_{ij}y_j-bv_{fi}-\sum k_i[g_i]^- +s_i\\
T_a\dot{v}_{fi}+v_{fi} &= y_{fi}\\
y_{fi} = [x_{fi}]^+ &= \max(x_{fi},\ 0),\ (i = 1,\ 2,\ \cdots,\ n)
\end{aligned}
\tag{2}
$$

where $x_{e(f)i}$ is the inner state of the i-th neuron and represents the firing rate; $v_{e(f)i}$ is a variable which represents the degree of the adaptation (modulated by the adaptation constant b) or self-inhibition effect of the i-th neuron; the output of each neuron $y_{e(f)i}$ is taken as the positive part of x_i, and the output of the whole oscillator as $Y_{(out)i}$; $\sum w_{ij}y_i$ represents the total input from the neurons inside a neural network: the input is arranged to excite one neuron and inhibit the other, by applying the positive part to one neuron and the negative part to the other; the inputs are scaled by the gains k_i; T_r and T_a are time constants of the inner state and the adaptation effect of the i-th neuron respectively; b is a coefficient of the adaptation effect; w_{ij} is a connecting weight from the j-th neuron to the i-th neuron; s_i is an external input with a constant rate. Especially, w_{ij} (≥ 0 *for* $i \neq j$ *and* $=0$ *for* $i=j$) is a weight of inhibitory synaptic connection from the j-th neuron to the i-th and w_{ei}, w_{fi} are also a weight from extensor neuron to flexor neuron, respectively.

Eq. (2) can be rearranged as follows

$$
\begin{aligned}
&x''_{ei}+(\alpha+\beta)x'_{ei}+x_{ei}+\sum w_{ij}\{\alpha(|x_{ij}|+x_{ij})'/2+(|x_{ij}|+x_{ij})/2\}\\
&+w_{fi}\{\alpha(|x_{fi}|+x_{fi})'/2+(|x_{fi}|+x_{fi})/2\}+by_{ei}-s_{ei}\\
&+\sum k_i\{\alpha(|g_i|+g_i)'/2+(|g_i|+g_i)/2\}=0
\end{aligned}
$$

$$x''_{fi} + (\alpha+\beta)x'_{fi} + x_{fi} + \sum w_{ij}\{\alpha(|x_{ij}|+x_{ij})'/2 + (|x_{ij}|+x_{ij})/2\} \tag{3}$$
$$+ w_{ei}\{\alpha(|x_{ei}|+x_{ei})'/2 + (|x_{ei}|+x_{ei})/2\} + by_{fi} - s_{fi}$$
$$-\sum k_i\{\alpha(|g_i|-g_i)'/2 + (|g_i|-g_i)/2\} = 0$$
$$(\alpha = T_a/\sqrt{T_aT_r},\ \beta = T_r/\sqrt{T_aT_r})$$

Based on Eq. (3), we are able to design the output pattern of the neural oscillator.

B. The function of entrainment of neural oscillator

This subsection describes the intrinsic property of self-entrainment of the neural oscillator to verify if it can be used as a tool for adaptation to pattern regeneration. The entrainment and input/output properties of the oscillators are used to perform a variety of tasks with the same architecture, without any modeling of system or its environment [19]. According to Matsuoka's work [17], [18], the entrainment can be realized under stable oscillation conditions of the neural oscillator. For stable oscillations, if tonic input exists, T_r/T_a should be in the range 0.1~0.5, for which the natural frequency of the oscillator is proportional to $1/T_r$. And increasing the input gain, k_i, causes the output of neural oscillator to be entrained with the amplitude and natural frequency of the input signal.

Figs. 15 and 16 show the output, the Fast Fourier Transform (FFT), and phase plane trajectory of the neural oscillator under stable conditions mentioned above. Under the same stable condition, we tested the response to an arbitrary input to verify the property of entrainment of the neural oscillator with non-periodic signals. The output of the neural oscillator locked onto input signals well as shown in Figs. 17 and 18. This is the first observation of the robustness of the neural entrainment mechanism, which motivated us to apply the neural oscillator to goal-directed imitation requiring perceived pattern regeneration. Tuning some other parameters as well, this entrained output can be controlled so that it follows given desired signals as closely as possible. Thus, the neural oscillator in the form of the proposed self-adjusting adaptor turns out to be a powerful tool for achieving goal directed-imitation.

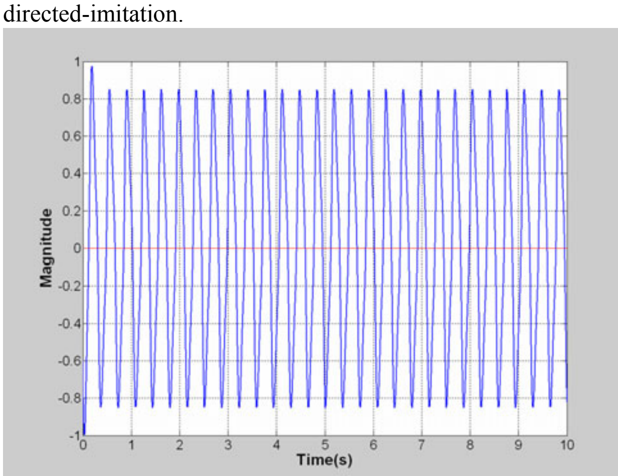

Fig. 15 Output of neural oscillator under a stable condition

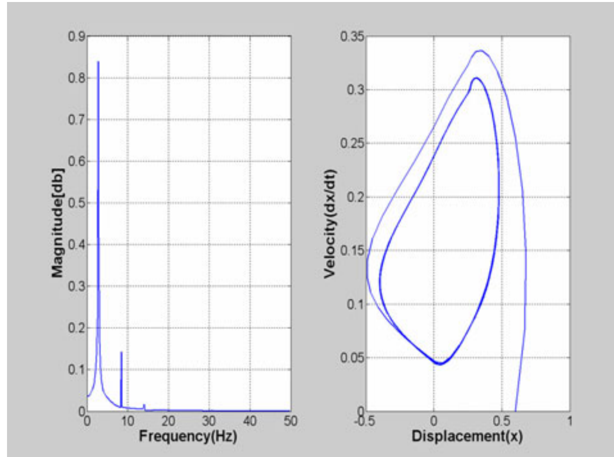

Fig. 16 FFT and limit cycle of neural oscillator output of Fig. 13

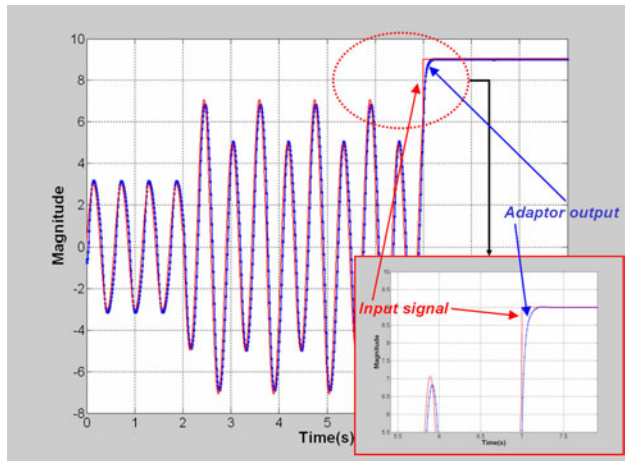

Fig. 17 Entrainment with a non-periodic input signal in self-adjusting adaptor

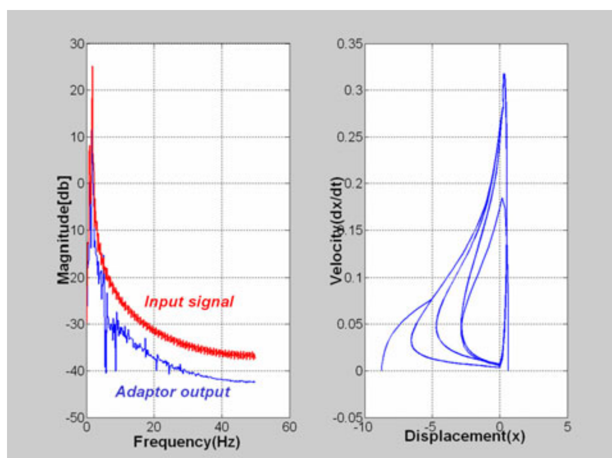

Fig. 18 FFT and limit cycle of input-output signals of Fig. 15

VI. Conclusions

This paper has presented an innovative framework for goal directed imitation using the self-adjusting adaptor, which employed a neural oscillator network. Existing works on imitation did not clearly address how to implement the program-level imitation between dissimilar bodies to achieve anticipated behaviors of the intended goal. Our object was thus centered around developing a practical methodology to imitate motions from dissimilar bodies. For this, the proposed self-adjusting adaptor regenerated the perceived motion trajectories into a new one which was adapted to the imitator's body considering the foot contact force direction. Particularly, the proposed imitation minimized the difference of the foot contact force between the demonstrator and the imitator and the number of data needed to be perceived. In addition one of the most important advantages of using the neural oscillator based adaptor is that neural oscillator can entrain with the external signals. The property of entrainment of the neural oscillator was investigated with different signals by tuning parameters under stable conditions.

From the current simulation results, it can be observed that the proposed method transferred perceived data properly into the appropriate imitator data which can achieve the goal of the perceived behavior. Also, the output of the self-adjusting adaptor locks onto the transferred imitation data well. To the best of the authors' knowledge, this is the first time that such a biologically inspired approach for imitation has been reported. This approach is a unique contribution to the realization of the program-level imitation, allowing it to maintain the intended goal of the perceived motion. Relating to future research, we will extend to various dynamic motions in 3-D environments and verify the practical validity of this approach through experiments with real robots.

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