Adaptive Combinatorial Neural Control for Robust Locomotion of a Biped Robot

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Abstract. Humans can perform natural and robust walking behavior. They can even quickly adapt to different situations, like changing their walking speed to synchronize with the speed of a treadmill. Reproducing such complex abilities with artificial bipedal systems is still a difficult problem. To tackle this problem, we present here an adaptive combinatorial neural control circuit consisting of reflex-based and central pattern generator (CPG)-based mechanisms. The reflex-based control mechanism basically generates energy-efficient bipedal locomotion while the CPG-based mechanism with synaptic plasticity ensures robustness against loss of global sensory feedback (e.g., foot contact sensors) as well as allows for adaptation within a few steps to deal with environmental changes. We have successfully applied our control approach to the biomechanical bipedal robot DACBOT. As a result, the robot can robustly walk with energy efficiency and quickly adapt to different speeds of a treadmill.

1 Introduction

Human locomotion is a complex process that results from the interaction of neural control and biomechanics [1],[2]. While biomechanics allows for natural movements, neural control, on the other hand, plays a role in generating different locomotion patterns with energy efficiency as well as assuring that a proper pattern can be quickly employed to, for instance, adapt to terrain change. This process is fast and adaptive which leads to the generation of natural robust locomotion and adaptation. During the last few decades, roboticists have tried to imitate such complex abilities with artificial bipedal systems. Although different bipedal robot systems have been developed, most of them is based on engineering control techniques like trajectory-based methods with precise joint-angle control [3],[4],[5],[6]. This results in non human-like locomotion (i.e., walking with bending knee) and high energy consumption. Others use biologically-inspired control mechanisms where global sensory feedback, like foot contact signals, is continuously used for generating coordinated walking behavior [7],[8],[9],[10]. Thus, the absence of the feedback can lead to unstable locomotion or failure. If learning mechanisms for adaptation are applied, then conventional machine learning techniques are normally employed [11],[12],[13],[14],[15]. Such learning techniques are usually complex and require an off-line learning process.

To tackle this problem, we present here a minimal adaptive combinatorial neural control approach coupled with biomechanics of our bipedal robot DACBOT. This control approach combines two main control modules: Reflex-based and CPG-based control modules. While the reflex-based control module [9] generates natural and energy-efficient locomotion, the CPG-based control module with synaptic plasticity allows for fast online adaptation to walk on different treadmill speeds as well as ensures robust locomotion against loss of (global) sensory feedback (e.g., foot contact sensors).

The paper is organized as follows. First, we describe the adaptive combinatorial neural control approach. Second, we present a setup of the biomechanical bipedal robot DACBOT. Third, we illustrate the performance of the control approach focusing on robust and adaptive walking on a treadmill at different speeds. Finally, we provide conclusion and discuss future work.

2 Adaptive Combinatorial Neural Control

The adaptive combinatorial neural control (Fig. 1) with a modular architecture consists of two main neural modules: CPG-based and reflex-based neural control modules (see subsections below for the details of each module). The idea behind this control approach is to first use the reflex-based control module to find and generate a proper walking frequency of a bipedal robot with respect to its property and the environment. Simultaneously, the CPG-based control module with synaptic plasticity learns the generated walking frequency and can later control the robot for robust walking behavior even without sensory feedback.

According to this concept, at the beginning the reflex-based control generates locomotion based on joint angle and foot contact sensory feedback for the biomechanical bipedal robot DACBOT. While the robot is walking, the CPG-based control uses only hip angle feedback to adapt its internal frequency to match the walking frequency generated by the reflex-based control. When the reflex-based control is disconnected (manually or due to sensory failure), the CPG-based control can still drive the robot. As long as the hip angle feedback is applied to the CPG-based control, the control can adapt its internal frequency to walking behavior with respect to the environment. If the feedback is removed from the CPG-based control, the robot will still be able to stably walk with the adapted walking frequency.

2.1 Reflex-based Neural Control

The reflex-based neural control, developed in our previous study [9] for biped locomotion, is a sensor-driven neural network with a hierarchical design. It is simulated as mono-synaptic connections containing motor neurons for hip and

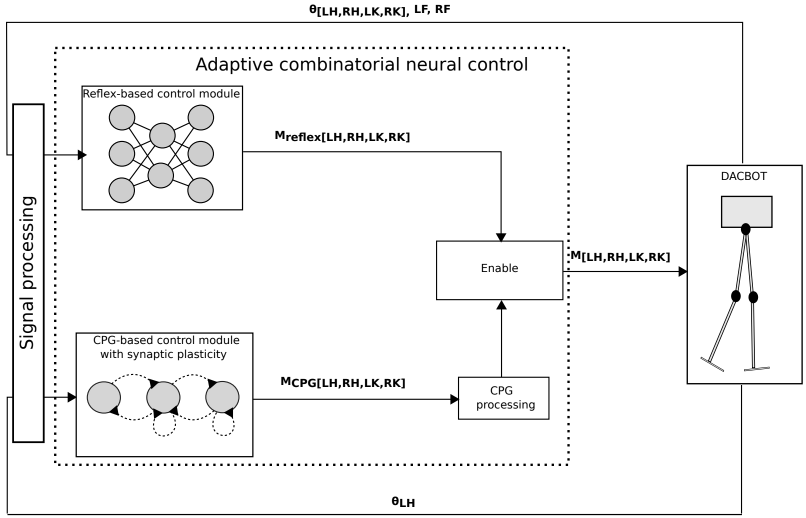

Fig. 1. The adaptive combinatorial neural control uses reflex-based neural control and CPG-based neural control with synaptic plasticity to generate energy-efficient, robust, and adaptive locomotion of a biped robot, like DACBOT. The reflex-based control generates the motor outputs ($M_{reflex[LH,RH,LK,RK]}$) by using all sensory information: Left/right hip angle feedback ($\theta_{LH,RH}$), left/right knee angle feedback ($\theta_{LK,RK}$), and left/right foot contact feedback (LF, RF). When the reflex-based control drives the robot system, the CPG-based control uses only hip angle feedback (e.g., the left hip (θ_{LH})) to adapt its internal frequency to generate the motor outputs ($M_{CPG[LH,RH,LK,RK]}$). A CPG processing unit is used to shape the CPG motor outputs by using threshold functions to obtain proper patterns for locomotion control. The shaped patterns follow the ones generated by the reflex-based control. An enable unit selects (manually or due to sensors failure) either the reflex motor outputs or the CPG motor outputs and transmits the selected motor outputs ($M_{[LH,RH,LK,RK]}$) to finally control the robot. Note that raw sensory signals are firstly preprocessed at a signal processing unit and then transmitted to the reflex-based and CPG-based control units. We use a low pass filter to remove sensory noise at the processing unit.

knee joints ($M_{reflex[LH,RH,LK,RK]}$, see Fig.2(a)). The motor neurons are linear and can send their signals unaltered to the motors of a biped robot. Furthermore, there are several local non-spiking sensory neurons (rate coded neurons), which by their conjoint reflex-like actions trigger the walking pattern. These local sensor neurons are for joint control, intrajoint control and leg control. Joint control arises from sensors at each joint (ES, FS), which measure the joint angle and influence only their corresponding motor neurons. Intra-joint control is achieved from sensors, which measure the anterior extreme angle (AL, AR) at the hip and trigger an extensor reflex at the corresponding knee. Leg control comes from ground foot contact sensors (GL, GR), which influence the motor neurons of all joints. In general, the reflexive locomotion generation works as follows: When one foot touches the ground, the hip extensor and knee flexor of the other leg (swing leg) are triggered, as well as the hip flexor and knee extensor of the stance leg. When the hip stretch receptor of the swing leg is activated, the extensor of the knee joint in this leg is triggered. Finally the foot of the swing leg touches the ground and the swing leg and the stance leg swap their roles thereafter. The generated motor patterns of the controller can be seen at Fig. 2(b).

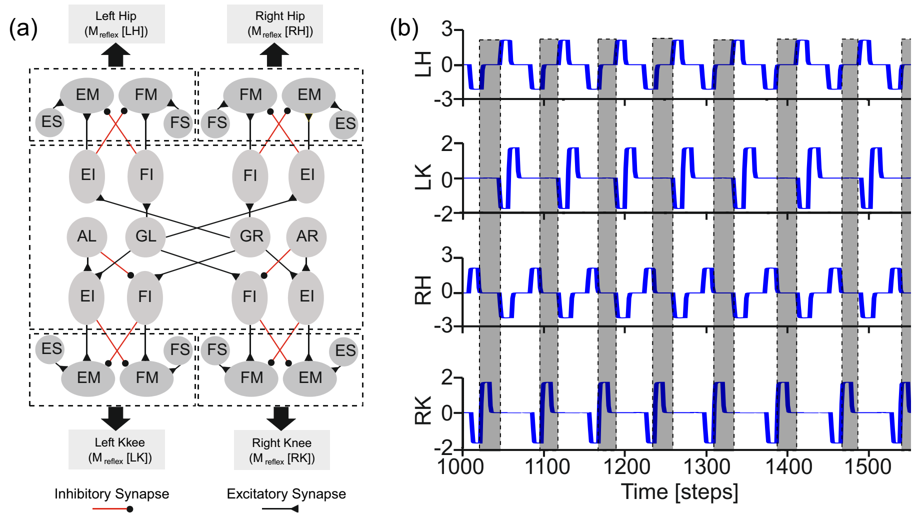

Fig. 2. (a) The reflex-based neural control coupled with biomechanics for generating energy-efficient locomotion of the bipedal robot DACBOT. $AL(AR)$ refers to stretch receptor for anterior extreme angle of left (right) hip. $GL(GR)$ refers to ground contact sensor neuron of left (right) foot. $EI(FI)$ refers to extensor (flexor) reflex interneuron. $EM(FM)$ refers to extensor (flexor) motor neuron and $ES(FS)$ is extensor (flexor) sensor neuron. (b) Energy-efficient walking of DACBOT. The motor outputs ($M_{reflex[LH,RH,LK,RK]}$) are directly sent to the robot through amplifiers. Gray areas indicate when all four motor outputs (corresponding to motor voltage) remain zero during part of every step cycle; i.e., DACBOT walks passively.

Further details of the controller are not subject of this study, but can be found in [9]. Although the reflex-based neural control coupled with biomechanics of DACBOT can generate energy-efficient locomotion (see Fig.2(b)), it fails if sensory feedback is not provided. Thus, here we apply the CPG-based neural control (Fig. 3) to overcome this problem. For energy-efficient locomotion in our study here, we implies that the robot does not require energy all the time during walking; i.e., it has partly passive locomotion (here, approx. 32% of one gait cycle, see gray areas in Fig.2(b)) where all actuators are not actively actuated (receiving zero voltage).

2.2 CPG-based Neural Control

The CPG-based neural control (Fig. 3(a)), developed in our previous study [16], consists of three rate codded neurons with a hyperbolic tangent (tanh) transfer function. The two neurons ($H_{0,1}$) are fully connected with the four synapses ($\omega_{00}, \omega_{01}, \omega_{10}, \omega_{11}$). This forms an oscillator if the synaptic weights are chosen according to an SO(2)-matrix [17]:

$$\mathbf{W} = \begin{pmatrix} w_{00} & w_{01} \\ w_{10} & w_{11} \end{pmatrix} = \alpha \cdot \begin{pmatrix} cos(\varphi) & sin(\varphi) \\ -sin(\varphi) & cos(\varphi) \end{pmatrix}. \tag{1}$$

With $-\pi < \varphi < \pi$ and $\alpha > 1$, the oscillator generates sine-shaped periodic outputs ($o_{0,1}$) of the neurons ($H_{0,1}$) where φ defines a frequency of the signals. The third neuron (H_2) receives sensory feedback (F_{CPG}) through the plastic synapse (ω_{2F}) and connects to the oscillator through the other plastic synapses (ω_{02}, ω_{20}). For convenience, we use here the left hip angle signal (θ_{LH}) of DACBOT as the feedback. These plastic synapses are governed by Hebbian-type learning rules based on correlation and relaxation terms driving the weights towards given relaxation values ($\omega_{2F_{relax}}, \omega_{02_{relax}}, \omega_{20_{relax}}$). The parameters A, $B > 0$ determine the influence of the individual terms [16]:

$$\omega_{2F}(t+1) = \omega_{2F}(t) + A \cdot F_{CPG}(t) \cdot o_2(t) - B \cdot (\omega_{2F}(t) - \omega_{2F_{relax}}), \tag{2}$$
$$\omega_{02}(t+1) = \omega_{02}(t) - A \cdot o_0(t) \cdot o_2(t) - B \cdot (\omega_{02}(t) - \omega_{02_{relax}}), \tag{3}$$
$$\omega_{20}(t+1) = \omega_{20}(t) - A \cdot o_2(t) \cdot o_0(t) - B \cdot (\omega_{20}(t) - \omega_{20_{relax}}). \tag{4}$$

The parameter (φ, Eq. 1) is adapted based on the following frequency adaptation rule:

$$\varphi(t+1) = \varphi(t) + \mu \cdot \omega_{02}(t) \cdot o_2(t) \cdot \omega_{01}(t) \cdot o_1(t), \tag{5}$$

where μ is a learning rate, o_1 and o_2 are the outputs of the neurons ($H_{1,2}$), and ω_{01} and ω_{02} are synaptic weights (Fig. 3(a)). With an appropriate choice of the control parameters [16], the CPG-based control governed by above equations is able to adapt to sensory feedback (F_{CPG}) within a wide frequency range. As soon as the controller has adapted to the external frequency of the sensory feedback (F_{CPG}), the average correlation of o_2 (sensory feedback) and o_1 (controller output) is equal to zero. After adaptation, the sensory feedback can be removed from the controller while it maintains to oscillate at the adapted frequency.

Here, the output (o_1) of the CPG neuron (H_1) is used for controlling the hip and knee joints of DACBOT since after the adaptation process the output will be in phase with the reflex motor command. This will lead to smooth switching between the reflex-based and CPG-based control; thereby the dynamical stability of the system is still maintained. The final CPG output (o_1) is post-processed at a CPG processing unit to obtain the hip and knee motor patterns ($M_{CPG[LH,RH,LK,RK]}$, e.g., red line in Fig. 3(b)) that have exactly the same

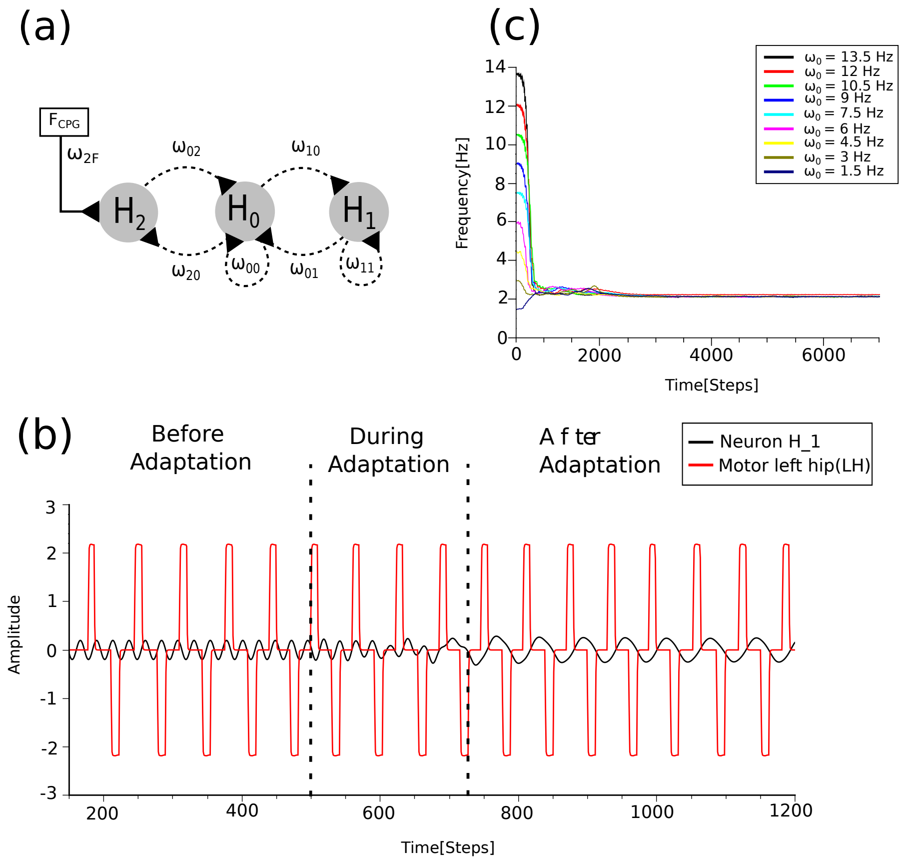

Fig. 3. (a) The CPG-based neural control with synaptic plasticity. The neurons ($H_{0,1,2}$) are connected through synaptic plasticity ($\omega_{00,01,10,11,20,02}$) to generate a periodic pattern with its internal frequency. The internal frequency can be entrained by an external feedback through the synaptic weight (ω_{2F}). By using the Hebbian-type learning rules (Eqs. 2, 3, and 4) and the frequency adaptation rule (Eq. 5) for synaptic plasticity, the CPG-based neural control can be entrained to quickly adapt its output frequency to the external frequency of sensory feedback and can memorize the adapted frequency although the feedback has been removed. (b) CPG and hip motor signals before, during, and after adaptation. The CPG-based control can quickly change its frequency within about 3-4 walking cycles. (c) Time series of the internal frequency changes during walking for different initial frequencies (ω_0). It finally converts to a proper walking frequency of DACBOT which is originally generated by the reflex-based control.

motor patterns ($M_{reflex[LH,RH,LK,RK]}$, see Fig. 2(b)) of the reflex-based control. The CPG-based control can quick adapt to the proper walking frequency of DACBOT and is not sensitive to an initial internal frequency (Fig. 3(c)).

3 Setup of the Biomechanical Bipedal robot DACBOT

DACBOT (Dynamic, Adaptive, Compliant walking robot) is a biomechanical bipedal robot which has been developed based on RunBot [9]. It is a 600g robot, 26 cm tall from foot to hip. Since the robot is designed for two-dimensional motion, a rod is used to constrain its movement and prevent lateral displacement; therefore, the robot can only rotate along the y-axis (Fig. 4(a)). DACBOT consists of two legs, where each leg is actuated by hip and knee joints. With a special design based on a human leg, each leg of DACBOT consists of a compliant ankle connected to a flat foot. It is mainly employed to realize dynamic and robust self-stabilization in a passive compliant manner. In addition, each foot has one switch sensor for ground detection as a binary feedback. The left and right hips are actuated by HS-624MG servomotors while the left and right knees are actuated by HS-85BB+ micro servomotors. The built-in controller of each servomotor was removed in order to directly control its DC motor and be able to read the angle feedback via its internal potentiometer sensor.

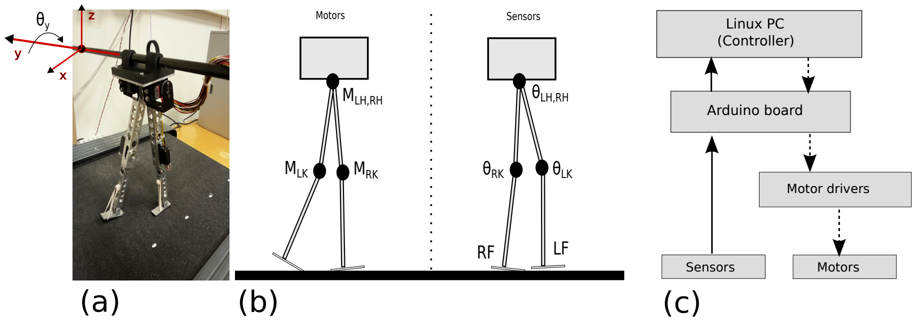

Fig. 4. (a) The planar bipedal robot DACBOT. For our experiments here, we constrain the robot such that it can only rotate along the y-axis. (b) Motors and sensors of DACBOT. (c) Schematic of the DACBOT setup.

The motor commands ($M_{LH,LK,RH,RK}$, Fig. 4(b)), generated by the adaptive combinatorial controller, are sent to the DACBOT motors through an Arduino UNO board and the Groove I2C Motor drivers. The sensory signals ($\theta_{LH,LK,RH,RK}$,LF,LH, Fig. 4(b)) are also digitized using this board for the purpose of feeding them into the controller. The schematic of the DACBOT setup can be seen at Fig. 4(c). A treadmill used to carry out our robot walking experiments has been modified so that its speed can be controlled through a computer.

4 Experiments and Results

Several experiments were carried out to show the performance of the adaptive combinatorial neural control. For the first experiment, we let DACBOT walk with the reflex-based control while the CPG-based control was disabled (Fig. 5). During walking, we then disabled a foot sensor at around 300 time steps. Since the CPG-based control was not activated, DACBOT failed to walk without foot contact feedback. In general, the reflex-based control can generate proper walking behavior when all sensory feedback ($\theta_{LH,RH,LK,RK}$, LF, RF) are provided, while it fails if any sensory feedback (e.g., foot sensor signal) is missing.

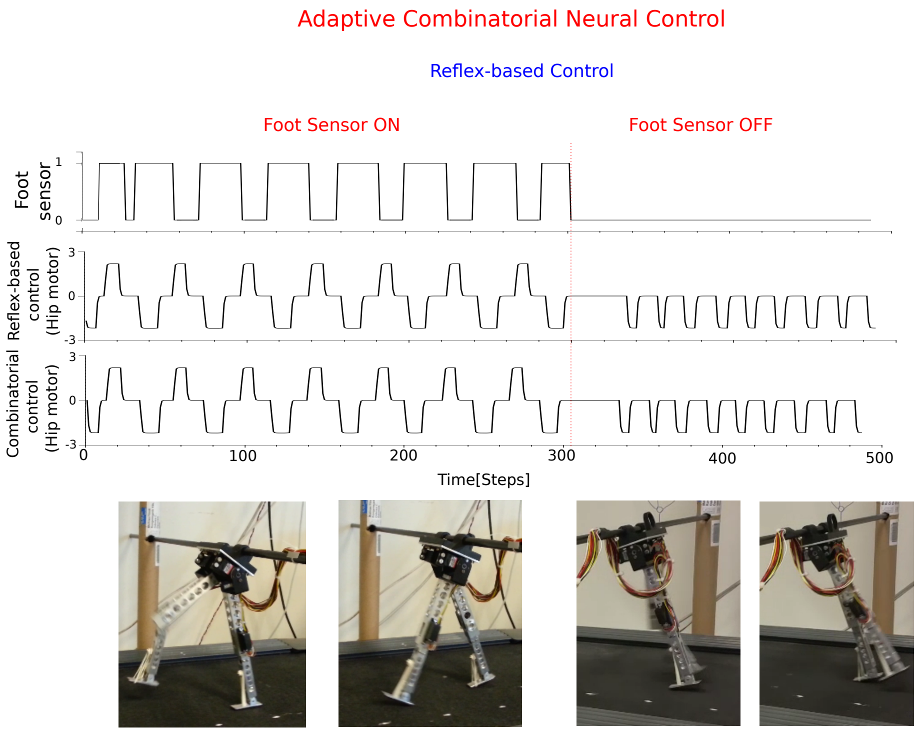

Fig. 5. DACBOT locomotion driven by only the reflex-based control of the adaptive combinatorial neural control. At the first period, all sensors were provided to the system. Therefore, the controller generated stable locomotion. Once a foot sensor has been disabled at around 300 time steps, the controller cannot generate proper motor signals. The top panel shows the left foot sensor signal. The middle panel shows a motor signal of the reflex-based control. The bottom panel shows the final motor signal controlling the left hip of DACBOT from the adaptive combinatorial control. In this case, since only the reflex-based control is used to drive the system, the combinatorial control has the same output as the reflex-based control. We encourage readers to watch the video clip of this experiment at http://manoonpong.com/SAB2016/M1.mp4.

For the second experiment, we let DACBOT walk with a combination of the reflex-based and CPG-based control (Fig. 6) where the reflex-based control drove DACBOT first and then the CPG-based control took over as soon as its frequency adapted to the walking frequency generated by the reflex-based control. Afterwards, we disabled a foot sensor at around 1000 time steps. Since DACBOT was driven by the CPG-based control after the frequency adaptation, it can still stably walk without foot contact feedback.

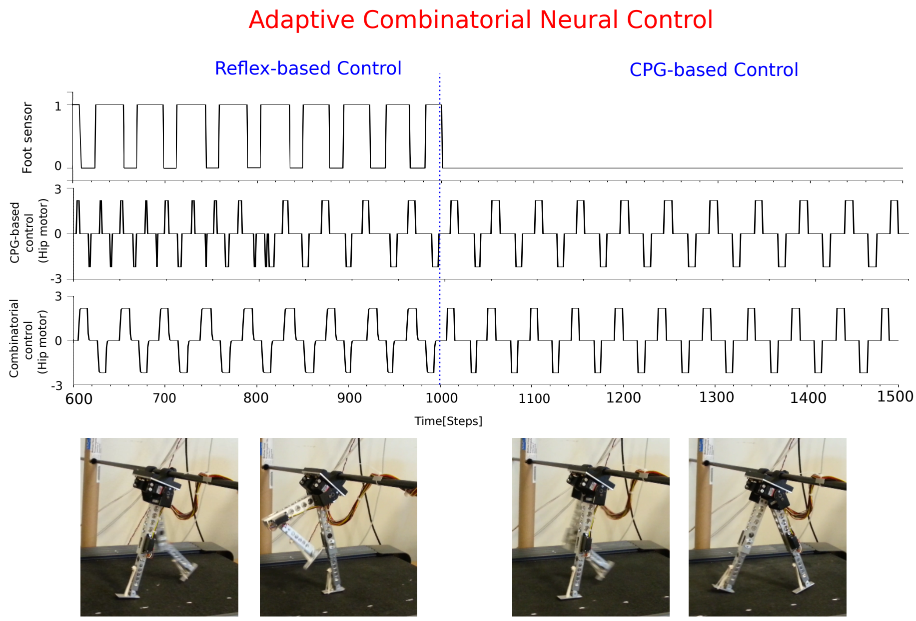

Fig. 6. Robust locomotion of DACBOT driven by the adaptive combinatorial control. Initially, the system was driven by the reflex-based control and simultaneously the CPG-based control adapted its internal frequency using the frequency adaptation mechanism with hip angle feedback to synchronize with the generated walking frequency. At around 1000 time steps, a foot sensor was disabled but DACBOT still performed robust locomotion driven by the CPG-based control. We encourage readers to watch the video clip of this experiment at http://manoonpong.com/SAB2016/M2.mp4.

The last experiment shows adaptive locomotion of DACBOT on different speeds of the treadmill. DACBOT was driven by the combinatorial control. The same procedure as the second experiment was performed with an extension of changing the speed of the treadmill after DACBOT was controlled by the CPG-based control where foot contact feedback was also disabled. We increased the speed of the treadmill from 0.09 m/s to 0.15 m/s and finally to 0.23 m/s. Figure 7 shows frequency adaptation and a hip motor signal with respect to the different situations. It can be seen that the controller can quickly react and adapt its output frequency to generate proper locomotion behavior. Recall that we used only a hip angle signal for the frequency adaptation process.

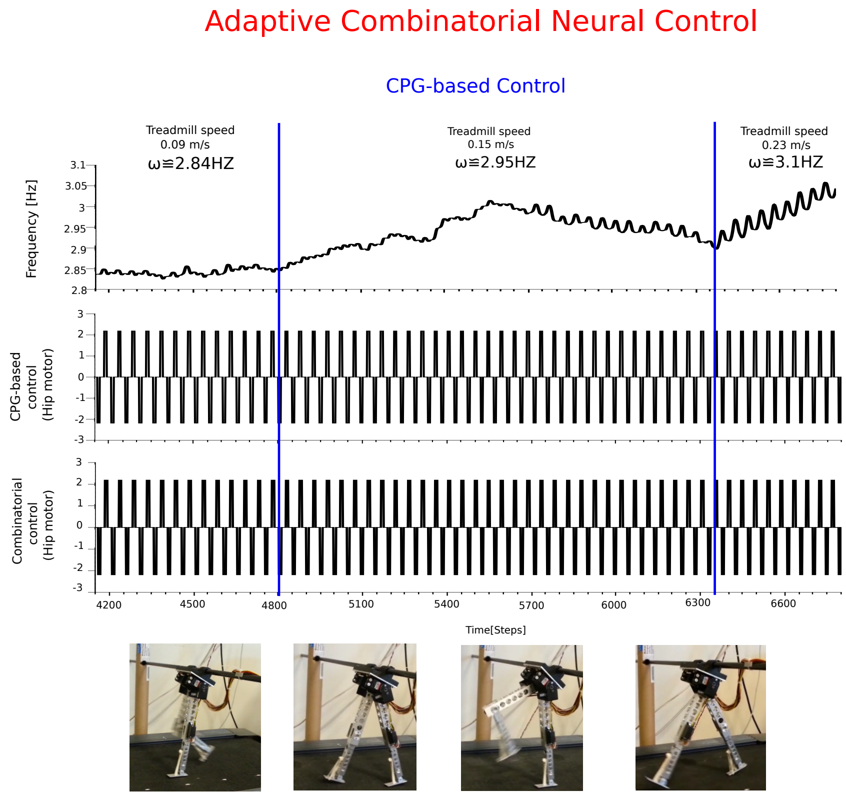

Fig. 7. Adaptation to three different speeds of the treadmill. Here DACBOT was controlled by the combinatorial control where the reflex-based control drove the system first and then the CPG-based control took over. Walking frequency was adapted according to the speed of the treadmill. The online frequency adaptation is obtained from the adaptation process of the CPG-based control with hip angle feedback. The top panel shows the internal frequency of the CPG-based control adapting to the different speeds of the treadmill. The middle panel shows a motor signal of the CPG-based control. The bottom panel shows the final motor signal controlling the left hip of DACBOT from the adaptive combinatorial control. This adaptation leads to different walking behaviors; i.e., DACBOT performed about six walking cycles within 300 time steps at 0.09 m/s, about seven walking cycles within 300 time steps at 0.15 m/s, and about eight walking cycles within 300 time steps at 0.23 m/s. Note that due to the robot dynamics, the CPG frequency can slightly increase and decrease although the treadmill is constant. We encourage readers to watch the video clip of this experiment at http://manoonpong.com/SAB2016/M3.mp4.

5 Conclusion and Future work

This paper presents the development of adaptive combinatorial neural control for a biped robot, like DACBOT. It combines reflex-based and CPG-based control mechanisms. Based on our control strategy, the reflex-based control firstly drives the robot system by exploiting sensory feedback and biomechanics of the robot to obtain proper walking frequency and leg coordination which results in energy-efficient locomotion. In parallel, the CPG-based control adapts its internal frequency to the actual walking frequency. Once the internal frequency of the CPG-based control has matched to the actual walking frequency or the CPG output has become in phase with the reflex output, the CPG-based control can be switched to control the system. Due to synaptic plasticity and a frequency adaptation mechanism embedded in the CPG-based control, DACBOT can quickly adapt its walking frequency to a change of the speed of a treadmill. For the adaptation, only a hip angle signal is required as sensory feedback to the CPG-based control while other sensory signals (e.g., knee and foot sensor signals) can be removed (as shown in the last experiment). This way, DACBOT performs adaptive locomotion with minimal feedback requirement. Furthermore, DACBOT can still perform robust locomotion at a certain walking speed even the hip angle signal has been removed from the CPG-based control. Such adaptive and robust locomotion cannot be achieved by purely reflex-based control [9] while proper initial walking frequency and leg coordination cannot be achieved by purely CPG-based control.

Some works combined CPG-based control with adaptive mechanisms (like, reinforcement learning [13] and evolutionary algorithms [14],[15]) for robust locomotion. However, such adaptive mechanisms need long learning time. In contrast, our control strategy with synaptic plasticity and the frequency adaptation mechanism can generate robust locomotion and online adaptation within a few steps to deal with environmental changes. Thus, this study shows that this novel and simple combinatorial control approach -presented here for the first time- may be a way forward to solve coordination problems and to achieve fast online adaptation with minimal feedback in other complex motor tasks for active prosthetic and orthotic devices. In the next step, we will implement a 2DOF upper body component on DACBOT and develop adaptive body control to allow DACBOT to walk with minimal movement constraints and to deal with large disturbance.

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