A combination of central pattern generator-based and reflex-based neural networks for dynamic, adaptive, robust bipedal locomotion

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Abstract: Robotic systems inspired from humans have always been lightening up the curiosity of engineers and scientists. Of many challenges, human locomotion is a very difficult one where a number of different systems needs to interact in order to generate a correct and balanced pattern. To simulate the interaction of these systems, implementations with reflex-based or central pattern generator (CPG)-based controllers have been tested on bipedal robot systems. In this paper we will combine the two controller types, into a controller that works with both reflex and CPG signals. We use a reflex-based neural network to generate basic walking patterns of a dynamic bipedal walking robot (DACBOT) and then a CPG-based neural network to ensure robust walking behavior.

Keywords: Central Pattern Generator, Bio-inspired robotics, Neural control, Embodied AI, Bipedal locomotion

1. INTRODUCTION

Bipedal locomotion has been of interest for the scientific community ([1], [2], [3], [4]). The most difficult part, still partially unsolved, is to reproduce stable and adaptable human-like locomotion for artificial systems ([5], [6]). Different bipedal robots were developed ([7], [8]) with closed-loop control of joint position. However, their generated locomotion is still non human-like locomotion in terms of dynamics, adaptivity, and robustness. The difficult problem faced by these systems is not only their design but also how to control them. Here, we propose adaptive combinatorial neural control for dynamic, adaptive, robust bipedal locomotion of a biomechanical robot called DACBOT which is a new generation of Runbot ([9]). The controller combines a reflex-based neural network ([9]) which generates dynamic and adaptive human-like locomotion ([10]) with a CPG-based neural network ([11]) which allows for robust locomotion even without sensory feedback.

2. THE DYNAMIC BIPEDAL WALKING 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. It is connected to a boom that constrains the robot in the roll and yaw direction. The treadmill was introduced to test robot walking behavior.

Figure 1 shows a schematic of DACBOT and the real setup, respectively. As shown, DACBOT is divided into two parts: An upper body part and a lower leg part. The upper body is composed of a servo motor carrying a weight and a gyroscope while the lower leg part has two legs. 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 manner. In addition, each foot has one switch sensor for ground detection as a binary feedback. The actuators used in the active joints are modified RC-Servo motors where the built-in control circuit was disconnected in order to control them as geared DC motors. The built-in potentiometer was modified to have the angle feedback of each motor providing to a controller.

This paper will be mostly focused on locomotion patterns. Therefore, the upper body will not be kept fixed at a certain position in all experiments. However, adaptive upper body control is currently being developed and will be applied in the future. As a preliminary study, we use Lpzrobots simulation ([12]) to simulate DACBOT and test our developed locomotion controller.

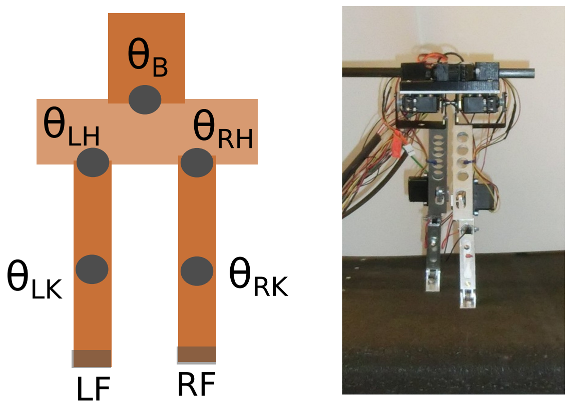

Fig. 1 Left: DACBOT schematic showing joints and feet. θ refers to an active joint. LF, RF are left and right foot contact sensors. Right: Real DACBOT setup.

3. ADAPTIVE COMBINATORIAL NEURAL CONTROL

The adaptive combinatorial neural control is a combination of CPG-based and reflex-based neural networks

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(Fig. 2). The reflex-based or reflexive neural network generates motor commands based on joint angle and foot contact feedback. While the network can generate dynamic and adaptive bipedal locomotion ([9]), it always fails if sensory feedback is not provided. Thus, here we apply the CPG-based neural network (Fig. 2) to overcome this problem. It consists of three neurons ($H_{1,2,3}$) with synaptic plasticity ($W_{00,01,10,11,20,02}$) ([11]).

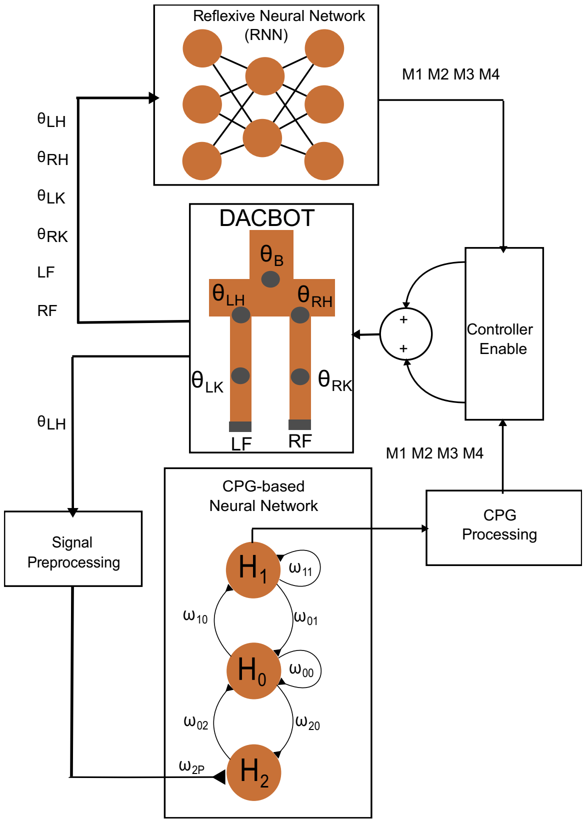

Fig. 2 The combination of the reflex-based or reflexive neural network ([10]) and the CPG-based neural network ([11]). They interact to drive the DACBOT system to achieve dynamic, robust, and adaptive locomotion. A controller enable is used to switch from reflex-based to CPG-based control and vice versa. $\theta_{LH,RH,LK,RK}$ are left hip, right hip, left knee, and right knee joint angle feedback. LF, RF are left and right foot contact feedback. $M_{1,2,3,4}$ are motor commands.

Figure 2 shows the schematic of the adaptive combinatorial neural controller. Here only a concept of the controller is given while the details of the reflex-based and CPG-based neural networks can be seen at ([10], [11]). The idea behind this controller is to use the CPG-based network to generate robust bipedal walking even without sensory feedback while the reflex-based or reflexive neural network can find and generate proper walking frequency according to the robot property and the environment.

At the beginning, the reflexive network generates locomotion based on joint angle and foot contact sensory feedback. While walking, the CPG network uses only hip angle feedback to adapt its internal frequency to match to walking frequency generated by the reflexive network. When the reflexive network goes off, the CPG network can drive the DACBOT system. As long as the hip angle feedback is applied to the CPG network, the network can adapt its internal frequency to walking behavior with respect to the environment. If the feedback is removed from the CPG network, DACBOT will still be able to stably walk with the entrained walking frequency.

Figure 3 shows a reflexive motor command controlling the left hip and the CPG outputs before and after adaptation. It can be seen that the synaptic plasticity-based adaptation process of the CPG network entrains its internal frequency to follow the reflexive one. Analyzing only one motor command is enough since all the motors have fixed phase relations. Here, we use the output of the CPG neuron H_1 for controlling DACBOT since after the adaptation process the output will be in phase with the reflexive motor command. This will lead to smooth switching between the reflex-based and CPG-based networks; thereby the dynamical stability of the system is still maintained. The feedback signal is filtered, centered around the zero, and scaled to the CPG network working range [-0.2,...,0.2].

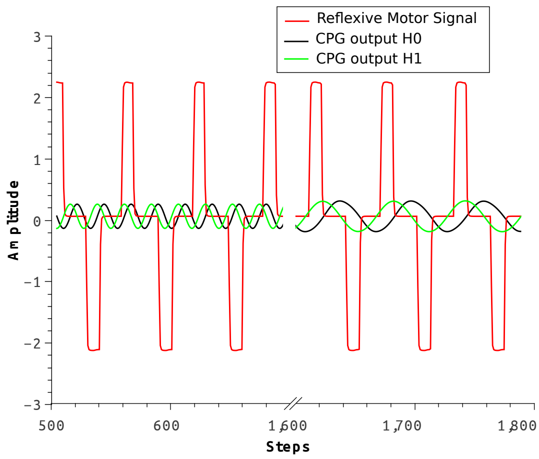

Fig. 3 Reflexive and CPG signals before and after adaptation process.

Figure 4 shows the generated motor signals for the hip and knee joints. The figure only shows signals for one leg. However, there is a fixed relation between the legs; therefore the computation of the two remaining signals is straightforward.

4. EXPERIMENTS AND RESULTS

Figure 5 shows frequency adaptation of the CPG-based neural network during a walking experiment. At the first period, DACBOT was driven by the reflexive neural network. The reflexive network can automatically generate basic DACBOT walking behavior as well as adapt the behavior to the environment. During walking, the CPG network with its arbitrary initial internal frequency (here, 6 Hz) adapted its internal frequency to follow the actual walking frequency. At around 2000 time steps, the CPG network was used to drive DACBOT in-

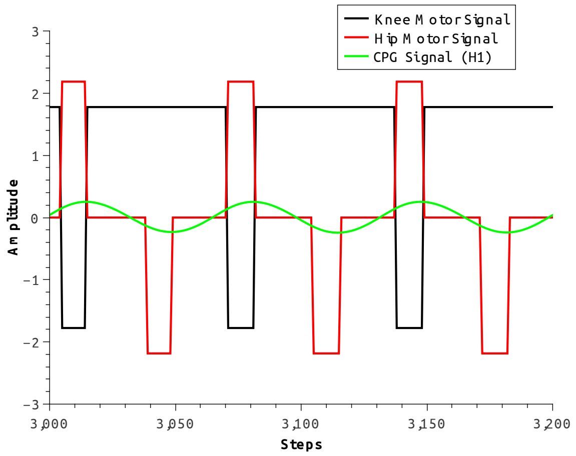

Fig. 4 Hips and knees motor signals generated by the CPG-based neural network.

stead where its frequency adaptation process still continued to fine tune the walking frequency. In this process, DACBOT could stably walk without any problem.

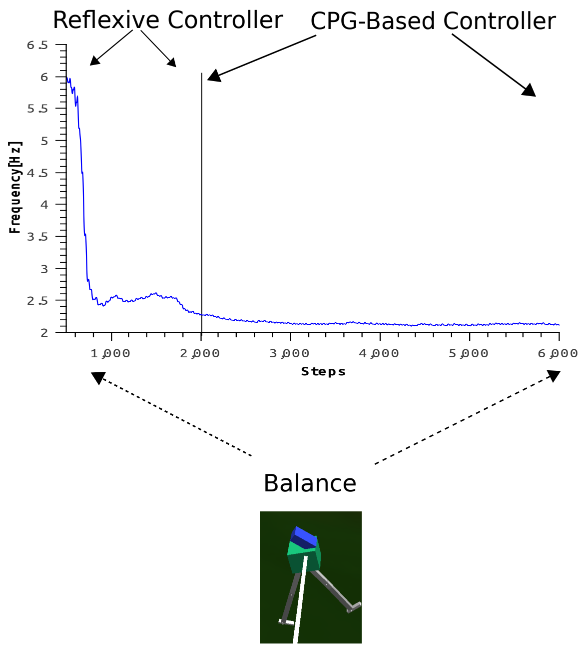

Fig. 5 Forced negative correlation of o_1 and o_2 after the adaptation process

Figure 6 shows robust walking behavior of DACBOT driven by the adaptive combinatorial neural controller where foot contact is the signal of the ground contact of the left foot, CPG signal is the signal from the CPG network controlling the left hip, hip angle is the angular position of the left hip, reflexive signal is the left hip motor position generated by the reflexive network, and Ext. Per is the hip sensory feedback applied to the CPG netwrok for entrainment. From steps 1000 to 2000, the reflexive signal drove DACBOT while the CPG was adapting its internal frequency to follow the frequency of Ext. Per. At step 2000, the reflexive signal went off as well as the foot contact was not provided anymore. In this situation, the CPG network took over to drive DACBOT. If any perturbation is applied (e.g., ground change), the CPG network can adapt its frequency to generate proper walking frequency to deal with the environmental change. At step 4000, Ext. Per was set to zero; thereby the CPG network drove DACBOT without any sensory feedback. It can be seen that DACBOT could still stably walk. We encourage readers to watch the video clip of the robot experiment at http://www.manoonpong.com/SW2015/SVideo.wmv.

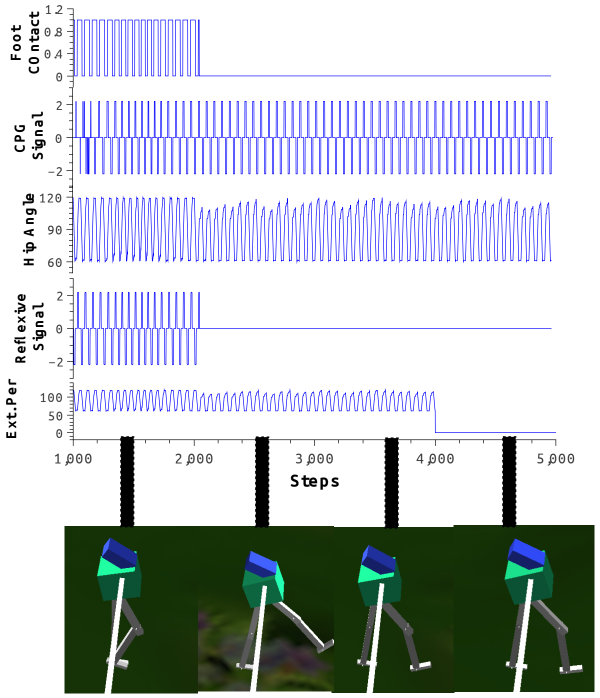

Fig. 6 Overall system behavior.

5. CONCLUSIONS

This paper presents the development of the adaptive combinatorial neural locomotion controller that combines reflex-based and CPG-based neural networks for adaptive and robust locomotion of the dynamic bipedal walking robot DACBOT. The robot is essentially composed by an upper part where a servo motor is carrying a weight to simulate the human upper body and a lower part with two segmented legs and passive compliant ankles. The legs have active hip and knee joints driven by micro servomotors and the passive ankles have springs for compliance. All the experiments were done by using the Lpzrobots simulation tool. Based on our control strategy, the reflex-based or reflexive neural network firstly drives the DACBOT system and adapt walking behavior of the system to the environment while the CPG-based neural network adapts its internal frequency to the actual walking frequency. Once the internal frequency of the CPG network has matched to the actual walking frequency or the CPG output has become in phase with the reflexive output, the CPG network can be switched to control the system. The experimental results show that the CPG network can quickly adapt to a walking frequency driven by the reflexive network. After the adaptation process, the CPG network can drive the system without sensory feedback. Although in this study we performed the robot walking experiments only on flat terrain, our previous study has shown that such passive compliant ankles used for DACBOT can provide robust self-stabilization to disturbances, like a sudden bump or a small obstacle placed on the flat terrain ([13]). For large disturbances, active upper body control will be required ([10]). In the next step, the controller will be extended with two CPG networks, one per each leg and with a phase coupling network. In addition, the results obtained in the simulation will be tested on the real hardware.

6. ACKNOWLEDGEMENTS

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