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A computational model for ratbot locomotion based on cyborg intelligence ☆

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ABSTRACT

Ratbots with electric stimulation in their brains possess not only their own biological sensation, perception, memory, and locomotion control abilities, but also machine visual sensation, memory and computing functionalities. With electrodes implanted in the medial forebrain bundle (MFB), we propose here a hybrid bio-machine locomotion system in the ratbots, processing the machine visual inputs, forming hybrid multiple memory system and outputting locomotion commands for navigation behaviors. To illustrate the enhanced performance of the ratbots theoretically, a computational model is presented to show how the multiple memory system affects the central pattern generator (CPG) generating the gait pattern and running velocity. Compared with the extensive data from behavioral experiments, the results output from the proposed computational model fit the data of the decision accuracy and the relative velocity well, thus shown that the model provides a possible locomotion control mechanism innately in the cyborg systems.

1. Introduction

Brain machine interface is becoming mature recently, which provides a promisingly enabling way to realize the direct interconnections between biological brains and computing modules. The novel concept of cyborg intelligent systems which integrate the biological intelligence with the artificial intelligence has been presented [1]. With the mutual integration and advantage complementation between brains and machines, cyborg intelligent systems can obtain more powerful capability to solve complex problems in the constantly changing circumstances, which neither biological nor artificial intelligence can settle alone. The Ratbot is a typical example of cyborg intelligent systems, which is a rat with electrodes implanted in its medial forebrain bundle area (MFB) to receive the electric stimuli from a computing system [2].

The neural circuitry that underlies vertebrate locomotion includes supraspinal systems and spinal networks [3]. The supraspinal systems are responsible to initiate movements and determine locomotion directions, which are related to decision making and motor selection [4]. These structures function by activating centers dedicated to the control of locomotor outputs [5]. For example, one of such centers is the mesencephalic locomotor region (MLR), which was first described in cats and later found in many vertebrates from fishes to mammals [6]. The brainstem locomotor control system is believed to be organized serially with MLR neurons projecting to reticulospinal cells, which in turn send descending commands into spinal cord CPG neurons to generate locomotion. The MLR neurons in the supraspinal systems thereby control the gait pattern and locomotion velocity precisely.

The spinal networks also known as central pattern generators (CPGs) are responsible for producing coordinated activation of muscles and thereby controlling propulsion [7]. The CPG is a biological neural circuit located in vertebrate spinal cord or invertebrate ganglion, which can produce rhythmic movements, such as walking, running, respiration, chewing, and heartbeat [8]. Movement patterns of neural activity are controlled by CPG networks with appropriate sequences of muscle activation to accommodate various gait patterns [9].

To better understand the ratbot performance and improve the design of bionic robots, a mathematical and computational model for ratbot locomotion is proposed in this paper based on supraspinal systems and CPG spinal networks as shown in Fig. 1. The high level supraspinal control system is modeled as a hybrid bio-machine MPMS

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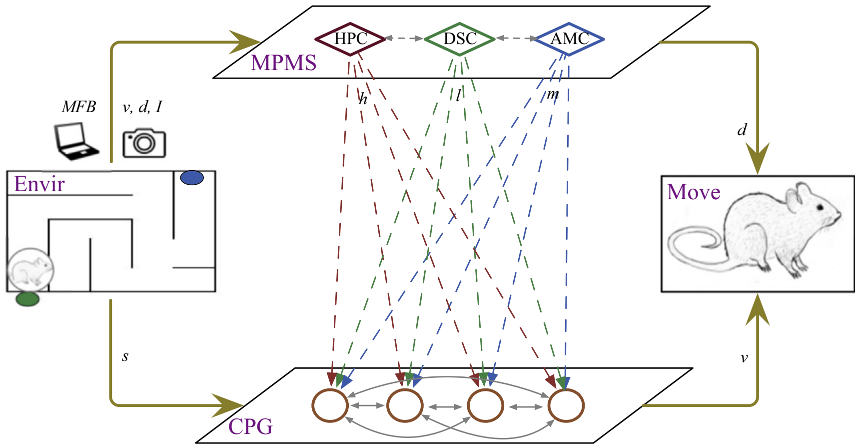

Fig. 1. Framework of the computational model for ratbot locomotion.

which consists of the hippocampus subsystem, the dorsal striatum subsystem, and the amygdala subsystem modulated by the computer-delivered MFB stimuli [10]. Based on the external environment information (v, d, I) captured by the camera and the computer-delivered simulation *MFB*, the hybrid bio-machine MPMS model will make the decision and select the optimal locomotion direction *d*. In cooperation with the modulation signals encoded by the hybrid bio-machine MPMS model (h, l, m), the higher supraspinal control system generates excitatory or inhibitory modulation signals to the brainstem motor center to regulate the intensity of MLR [3,11]. The MLR neurons project to reticulospinal cells which send descending commands to spinal cord CPG neurons to control gait modes and locomotion velocity v [6]. Under the balance between MPMS system and CPG networks, the adaptive motion is produced for ratbots in locomotion initiation, motion integration and action selection. Finally the ratbots navigate in the maze to reach the goal position.

The remainder of this paper is structured as follows. In the next section, we will briefly introduce the hybrid bio-machine MPMS in our computational model. And then the CPG model with MLR modulation signals from the MPMS is described in Section 3 in detail. Evaluation of the proposed model is demonstrated and discussed in Section 4, using typical maze learning tasks. At last, this paper ends with a brief conclusion and discussion in Section 5.

2. Locomotion direction modulated by the hybrid bio-machine MPMS model

As shown in Fig. 1, the high level supraspinal control system is modeled by a hybrid bio-machine MPMS, with the hypothesis of three central structures (the hippocampus, the dorsal striatum and the amygdala) [12,13]. The hybrid bio-machine MPMS in ratbot is constructed as a combination of the neural circuits in rat brain and the MFB reward loop delivered by the computer. In the hippocampus subsystem, the external environment stimuli and the internal proprioception information are processed. In the dorsal striatum subsystem, the landmark information is encoded. And in the amygdala subsystem, the real-time MFB stimulation calculated by the computer is modeled.

In our model, the hippocampus subsystem is constructed based on the hippocampal place cells [14–16], which includes two kinds of space information. In the allothetic and idiothetic pathway, distances to the walls and proprioceptive inputs (rat own speed and head direction) are processed respectively [17]. Both allothetic hippocampus cells (APCs) and idiothetic hippocampus cells (IPCs) are projected into hippocampus cells (HPCs) to represent current position [16]. For a HPC cell k, we calculate its activity using the following equation with inputs from the two different representations of spatial information in APCs and IPCs:

$$v_k^H = \sum_{i=1}^{n_A} w_{mi} * v_i^A + \sum_{j=1}^{n_I} w_{mj} * v_j^I \tag{1}$$

where v_i^A and v_j^I are the activity of the APC cell i and IPC cell j respectively. The weights w_{mi}, w_{mj} between HPC m and APC i, IPC j are updated using Hebbian learning algorithm [18]:

$$\Delta w_{mi} = \mu * v_m^H * (v_i^A - \Delta w_{mi})$$
$$\Delta w_{mj} = \mu * v_m^H * (v_j^I - \Delta w_{mj}) \tag{2}$$

where μ is the learning rate, v_i^A, v_j^I and v_m^H are the activity of the APC cell i, IPC cell j and HPC cell m respectively.

The striatum subsystem encodes the landmark information and makes a connection between the landmark and a specific action when the landmark and the reward appear in pairs [17]. The landmarks information is processed by a population of landmark cells (LCs). If there is a landmark detected in one direction, the activity of LC in that direction is 1, otherwise is 0. The firing rate of the DSC populations is computed as

$$v_j^D = \exp\left(-\frac{\sum_{k=1}^{n_L} (I_k^L - I_k)^2}{n_L * 2\sigma_D^2}\right) \tag{3}$$

where $(I_1^L, I_2^L, \ldots, I_{n_L}^L)$ are the representation of landmark in n_L directions for the DSCs, I_k is the current view in DSCs.

With inputs of rat action a and current state s captured by the camera of the computer at time t, the environment Q value $Q(s_t, a_t)$ is calculated by a Q learning algorithm running on the machine as follows:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha(r_t + \beta Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)) \tag{4}$$

where r_t is the reward, α is the learning rate and β is the discount factor which determines the current value for future rewards. For state s_t, the computer calculates the $Q(s_t, a_t)$ and delivers the MFB stimulus intensity *SI* mapping from the $Q(s_t, a_t)$ [19,10].

A population of action cells (ACs) receives the projections from HPCs and DSCs to calculate the movement direction angle ϕ of the agent (i.e., the rat or the ratbot):

$$v_l^A = \sum_{i=1}^{n_H} w_{li} * v_i^H + \sum_{j=1}^{N_D} w_{lj} * v_j^D \tag{5}$$

where v_l^A denotes the activity of action cell l, $l = 1, \ldots, n_A$, v_i^H and v_j^D are the activity of the HPC i and the DSC j, which are calculated in Eqs. (1) and (3). The weights w_{li} and w_{lj} between AC l and HPC i,