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A Legged Central Pattern Generation Model for Autonomous Gait Transition

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***Abstract*—In this work, a generalized central pattern generator (CPG) model is formulated to generate a full range of gait patterns for a hexapod insect. To this end, a recurrent neural network module, as the building block for rhythmic patterns, is proposed to extend the concept of oscillatory building blocks (OBB) for constructing a CPG model. The model is able to make transitions between different gait patterns by simply adjusting one model parameter. Simulation results are further presented to show the effectiveness and performance of the CPG network.**

I. Introduction

THE constituents of the locomotive motor system are traditionally modelled by nonlinear coupled oscillators, representing the activation of the flexor and the extensor muscles driven by, respectively, two neurophysiologically simplified motor neurons [1-4]. Different types of oscillators can be chosen and organized in a designed coupling mode, and usually with appropriate topological shape to allow simulating the locomotion of particular animals [5-9]. All internal parameters or weights of coupled synaptic connections of the oscillator network are controlled by the environmental stimulations, central nervous system instructions and the network itself. The nature of the parallel and distributed processing is a prominent characteristic of this oscillatory circuit that can be canonically described by a set of ordinary differential equations (ODE), which may also be an autonomous system. In other words, a complex biological pattern generator system such as the well studied central pattern generators (CPG) can be simplified and implemented in a phenomenological model that uses the concrete artificial neural network dynamics.

Following our previous modelling [10-12] and implementation [13] works, a generalized locomotion CPG architecture is presented here not only to generate a range of legged gait patterns but also to make the transitions between different patterns. A mathematical formalism, extended from our previous works for gait pattern generation, is proposed to incorporate the gait pattern transitions. The CPG model uses an oscillatory building block (OBB) [12] as a pair of flexor and extensor motoneurons to drive individual joints. The interconnection of OBBs formulates a CPG model capable of generating different gait patterns and their transitions. It is also shown that only one OBB parameter is used to control the creation of different gait patterns, and gait pattern transition is therefore implemented by changing this OBB parameter.

The proposed CPG model provides a reconfigurable architecture to integrate many observed gait patterns of any legged animals. The scalability and modularity features make the model particularly amenable to hardware or software implementation. A computer simulation shows that the model is able to run smoothly for both single pattern operation and pattern transitions provided that its initial state is properly configured.

The rest of the paper is organized as follows. Section 2 derives a mathematical framework for the OBB module and the CPG model, which is suitable for the neuronal network design. Some simulation results are presented in section 3 to show its performance. Finally Section 4 concludes the work.

II. The Model

In this section a graph dynamics is first introduced, which is followed by the dynamics of a generalised OBB module description.

A. Graph Dynamics

Consider there is a neighbourhood-constrained system composed of a set of nodes and a set of shared resources represented by a connected graph G=(N,E) where N is the set of nodes, and E, the set of all resources between any pair of interconnected nodes. Between any two nodes i and j, i, j ∈ N, there can exist e_{ij} resources, $e_{ij} \geq 0$. The reversibility of node i is r_i, i.e., the number of resources that shall be reversed by node i towards each of its coupled nodes, indiscriminately, at the end of its operation. A node will operate if and only if it possesses r_i resources from all of its coupled nodes.

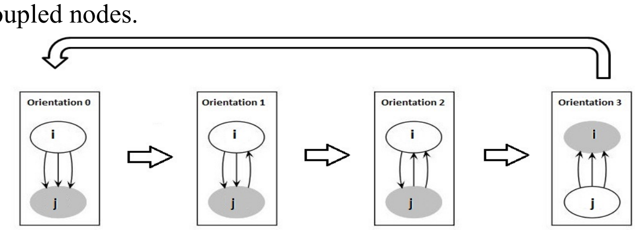

Fig. 1. An example of the graph dynamics. Node i and j have reversibility value as 3 and 1. Dark nodes indicate the sinks and white nodes for sources. A cycle of this graph dynamic system has 4 orientations. Node i becomes a sink exactly once, and node j becomes a sink 3 times in a cycle.

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The reversibility value for each coupled node needs to be chosen together with a suitable number of resources belonging to each node. Two criteria exist for the arrangement of coupling parameters to avoid starvation or deadlock of the period operation: (1) $\max\{r_i, r_j\} \le e_{ij} \le r_i + r_j - 1$. (2) $f_{ij} = r_i + r_j - \gcd(r_i, r_j)$. where f_{ij} is the sum of the greatest multiple of $\gcd(r_i, r_j)$ that does not exceed the number of shared resources oriented from n_i to n_j, and from n_j to n_i, respectively in the initial orientation. The first rule stipulates a range of the number of the resources while the second decides the exact number of resources in the range and their directions. Based on the two rules a dynamic attractor can be made with flexible control of its active patterns, and be immune of the system halt due to deadlock or starvation [14][15]. Figure 1 illustrates the graph dynamics.

B. Dynamics of an OBB Module

Inspired by the Hopfield Neural network model, the SMER graph dynamics can be described by a group of difference equations for computer simulation. Consider a pair of coupled neuron i and j with r_i and r_j as their reversibility, respectively. This coupled neuron pair is referred to as an OBB. The postsynaptic membrane potential of neuron *i* at *t* time instant, $M_i(t)$, depends on three factors, i.e., the potential at last instant $M_i(t-1)$, the impact of its coupled neuron output $v_j(t-1)$, and the negative feedback of neuron *i* itself $v_i(t-1)$, without considering the external impulses. The difference equation in the discrete time domain of this system can be formulated as follows: each neuron's self-feedback strength is $w_{ii} = -w_{ij}$, $w_{jj} = -w_{ji}$, and the activation function is a sigmoidal Heaviside type. Thus we have,

$$\begin{bmatrix} M_i(t) \\ M_j(t) \end{bmatrix} = \begin{bmatrix} M_i(t-1) \\ M_j(t-1) \end{bmatrix} + \underbrace{\frac{1}{r'} \times \begin{bmatrix} -r_i & r_j \\ r_i & -r_j \end{bmatrix}}_{W} \times \begin{bmatrix} v_i(t-1) \\ v_j(t-1) \end{bmatrix} \quad (1)$$

Where W is the weight matrix. We have the outputs of neurons as,

$$\begin{cases} v_i(t) = \max(0, \mathrm{sgn}(M_i(t) - \theta_i)) \\ v_j(t) = \max(0, \mathrm{sgn}(M_j(t) - \theta_j)) \end{cases} \quad (2)$$

The selection of system parameters, such as the neuron thresholds and synapse weights, are crucial for modelling the OBB module. In the model, let $r' = h(r)$, h is a function of getting highest integer level and multiplying by 10, e.g., let's suppose $r_i = 77$ and $r_j = 463$ then we have the function $h(r) = h(\max(77,463)) = h(463) = 10^3$. The neuron *i* and *j*'s thresholds θ_i and θ_j and their synaptic weights can be designed as $\theta_i = r_i / f_{ij}$, $\theta_j = 1 - \theta_i$, $W_{ij} = r_i / r'$, $W_{ji} = r_j / r'$. The model parameters can be arranged by comparing the two nodes' reversibility. If $r_i > r_j$, then $\theta_i > \theta_j$ and $w_{ij} > w_{ji}$ (i.e., asymmetric coupling), that means, a node with smaller reversibility, corresponding to a neuron with lower threshold in an OBB module, will oscillate at a higher frequency than its companion does.

The combination of the duty cycle (the ratio between the interval of the positive output and its associated oscillation period), the oscillation frequency and the phase latency of a coupled pair of neurons is the key set of joint parameters for modelling a one DOF joint. The oscillatory pattern transition, which is another important concept in addition to the pattern generation, can thus be understood as a transition from an old to a new set of the joint parameters. It is clear that the duty cycle of an extensor motor neuron plays an important role in deciding the locomotion speed of a legged animal [16-18]. In this model, the duty cycle of a neuron in a coupled two neuron system is dependent on the model parameters. The choice of reversibility of two coupled neurons thus dictates the transition between different patterns as it decides the model parameters, and hence the duty cycle. Therefore, the design of transition in patterns is simplified to the selection among different reversibility values.

Suppose both coupled neurons have their reversibility changed in the amount of r_i^d and r_j^d, respectively, the model formula (1) in a more general format involving pattern transition is as follows.

$$\begin{bmatrix} M_i(t) \\ M_j(t) \end{bmatrix} = \begin{bmatrix} M_i(t-1) \\ M_j(t-1) \end{bmatrix} + \left(W + \underbrace{\frac{s_i}{r'}\begin{bmatrix} -r_i^d & 0 \\ r_i^d & 0 \end{bmatrix} + \frac{s_j}{r'}\begin{bmatrix} 0 & r_j^d \\ 0 & -r_j^d \end{bmatrix}}_{\Delta W} \right) \times \begin{bmatrix} v_i(t-1) \\ v_j(t-1) \end{bmatrix} \quad (3)$$

where $s_k = \begin{cases} 1, & \text{if } r_k \text{ changed} \\ 0, & \text{if } r_k \text{ not changed} \end{cases}$. It is a transition control signal, $k \in (i, j)$.

The model parameters can be now transformed to:

$$\theta_i^{new} = (r_i + r_i^d) / f_{ij}^{new} \quad (4)$$

$$\theta_j^{new} = (r_j + r_j^d) / f_{ij}^{new} \quad (5)$$

$$W_{ij}^{new} = (r_i + r_i^d) / r' \quad (6)$$

$$W_{ji}^{new} = (r_j + r_j^d) / r' \quad (7)$$

$$f_{ij}^{new} = r_i + r_i^d + r_j + r_j^d - \gcd(r_i + r_i^d, r_j + r_j^d) \quad (8)$$

These equations indicate that, in theory, the pattern transition can be incurred by the reversibility change of any one of the two coupled neurons.

III. SIMULATION RESULTS

In this section, some case studies of the operations of the OBB modules, in the formats of a single OBB or a group of OBBs for the collective behaviours, are demonstrated in terms of the oscillatory patterns generation and transition.

A. Pattern Generation

Let's suppose that an OBB module has two coupled neurons i and j with the reversibility values $r_i = 3$ and $r_j = 12$. According to the algorithm, we have the module parameters as follows.

Table 1. OBB module parameters

	Neuron i	**Neuron j**
Reversibility	3	12
Weight[a]	0.03	0.12
Threshold	0.25	0.75
Initial value[b]	0.66	0.34

[a] The weights of Neuron i and j are W_{ij} and W_{ji}, respectively. [b]Initial membrane potential values are chosen randomly in the range of [0,1].

The oscillatory dynamics of the OBB module can be obtained by using Matlab Simulink, as shown in Figure 2A. It is noticeable that the coupled neurons start with a self-organised period with the given initial membrane potentials. The system then undergoes a stable periodic oscillation. The duty cycle of a neuron is decided by the model parameters, and thus indirectly related with the reversibility of two coupled neurons. The state space plot of this example is shown in Figure 2B.

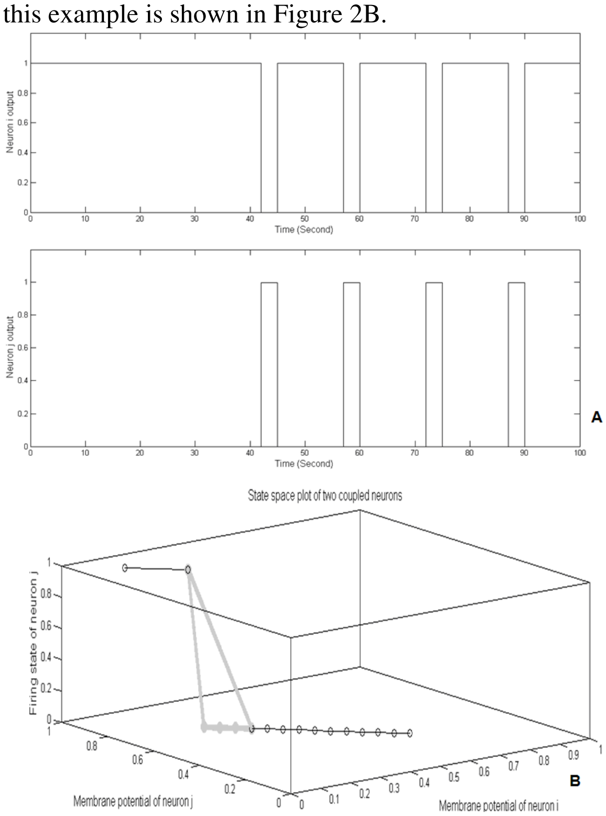

Fig. 2A. The waveforms of an OBB module in time domain. Upper panel : Neuron i output ; Lower panel : Neuron j output. When the system becomes stable, the oscillatory period is 15 seconds and the duty cycle of neuron i is 12 seconds. Fig. 2B. The state space plot of the periodic oscillation of an OBB module. The two axes on the planar surface represent the membrane potentials of two neurons, the vertical axis is for the firing state of neuron j. From different initial membrane potentials, the model evolves into a sequence of periodical states like a limit cycle.

B. Pattern Transition

As it is shown above, a change of the reversibility of any one of two coupled neurons results in the change of model parameters, and hence the change of oscillatory patterns. Therefore, the pattern transition in the OBB module is straightforward. In Simulink simulation, a control signal, corresponding to the control signal in formula *3*, is used to switch between the old and new model parameters derived from the old and new reversibility of the coupled neurons. For instance, if we need to change the reversibility of a pair of coupled neurons from $\{r_i = 3, r_j = 12\}$ to $\{r_i = 3, r_j = 3\}$, the dynamic model parameters are changed accordingly,

Table 2. OBB module parameters

	Old i	**Old j**	**New i**	**New j**
Reversibility	3	12	3	3
Weight	0.03	0.12	0.3	0.3
Threshold	0.25	0.75	1	0
Initial value	0.66	0.34	0.24	0.76

Like a switch being used to control the pattern change, a transition between old and new patterns can be achieved with some possible intermediate self-organization period (see Figure 3).

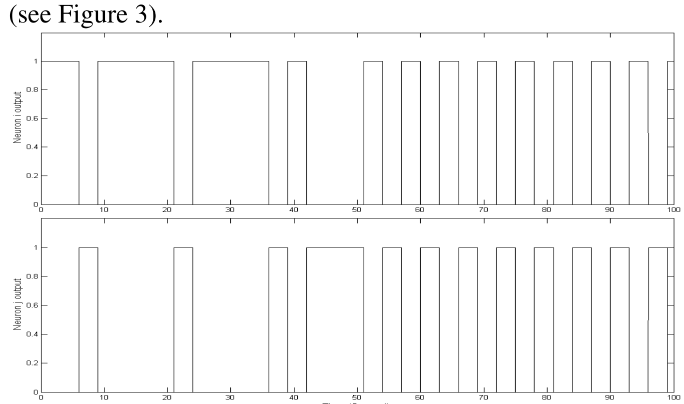

Fig. 3. A pattern transition process. The transition occurs at the time instant of 40, before when the pattern has the reversibility of $\{r_i = 3, r_j = 12\}$, and afterwards it has $\{r_i = 3, r_j = 3\}$.

It is clear that if no transition happens then neuron i will continue its first pattern, which becomes high at time instant 39 and lasts for 12 seconds till 51. The duty cycle for neuron i is 0.8 (and for neuron j is 0.2 accordingly). As a command for pattern transition occurs at 40, ideally the new pattern should start immediately after this time instant. Practically a self-organisation period exists such that the new pattern starts at the time instant of 51 second. This is because the membrane potentials of two coupled neurons are not ready (or more accurately, not as close as possible to their thresholds due to the operation of the old pattern) to make the transition to happen immediately. After a short period, though, the model will evolve into the desired new pattern with the duty cycle of neuron i as 0.5 (neuron j as 0.5). We argue that this phenomenon is biologically plausible as no real creatures will act immediately, i.e., zero delay, upon a command of action.

C. Simulation of Insect Legs

A demonstration of how to use the proposed algorithm to simulate the gait patterns and their transitions for the legged locomotion is briefly introduced here. The simplified hexapod structure is represented by 6 pairs of flexors (for nodes labeled F) and extensors (for nodes labeled E) working as 6 joints, one for each leg. This group of joints is used for driving a hexapod to move forward. More realistic hexapod legs should be driven by more groups of joints to move, e.g., up and down, though the underlying operation is the same as the flexor and extensor pairs proposed in this work. The nodes share a different number of resources represented by small white circles. The operation of a pair of nodes is controlled by SMER algorithm, in a same way as is shown in Figure 1.

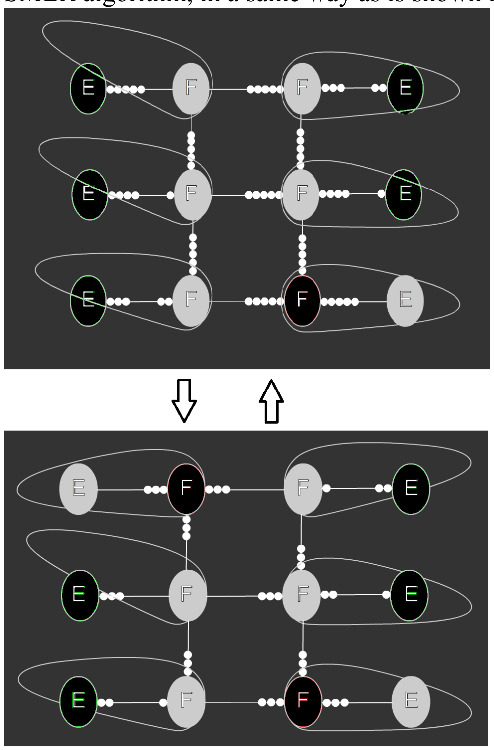

Fig. 4. Two snapshots of the running hexapod CPG structure for slow speed (upper panel) and medium speed (lower panel) locomotion. The black nodes denote the corresponding neurons are firing whilst the grey nodes are those which are idle. A pair of coupled flexor and extensor neurons follow the SMER algorithm to become firing or idle. The small white circles within each pair denote resources shared between nodes.

The animation shows that a transition between different gait patterns can happen if the the number of shared resources is reconfigured for the locomotion system. That is, in the slow speed locomotion the reversibility of the flexor and the extensor is 5 and 1, respectively while in the medium speed locomotion the reversibility of the flexor and the extensor is 3 and 1, respectively. Although for different gait patterns the number of inter-flexor resources is different, they are released to the coupled side as a whole since all flexors have the same reversibility. Therefore the use of resources between flexors can be treated as the glue to bind the 6 legs together to form a body of an insect. The implementation of the hexapod structure is straightforward and similar to the simulation of a single pair of flexor and extensor oscillators.

IV. Concluding Remarks

An extended OBB model that is able to be configured to build up a tailor designed architecture for both model generation and transition has been proposed in this work. The simple OBB module constitutes a basis from which a complex, rhythm-producing model can be designed. Due to adoption of the OBB module, the whole model can be modular and scalable for design, prototype, manufacture and test. It is also an asynchronous and self-clocked system if the reversibility values and initial membrane potentials are chosen for individual OBB modules. Because of the simplicity of the system, the hardware version of a simple OBB module can be made such that a system with arbitrary complexity can be hopefully developed for real-time hardware implementation.

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