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# Modeling of human gait control using CPGs

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**Abstract**—In this paper, a way of controlling musculoskeletal gait of human using central pattern generators (CPG) is presented. Our controller is able to produce healthy or altered gait in sagittal plane using musculoskeletal model with six joints and sixteen muscles. Controller consists of eight CPGs and it uses five types of sensory feedback. Simulation results in Matlab shows that changing intrinsic parameters of CPGs, model produces different types of gait.

**Keywords**—central pattern generator, musculoskeletal model, Parkinson’s disease, human walking

## I. INTRODUCTION

Parkinson’s disease is a neurodegenerative illness originating in death of dopamine-producing neurons in basal ganglia. While affected by this disease, person is marked by symptoms of tremor, muscle rigidity, freezing of gait and slow precise movements [1].

Nowadays, one can find models of human gait affected by Parkinson’s disease. But they lack simulation of lower structures implied in movements, such as muscles and spinal neuron networks called central pattern generators (CPG).

The aim of our work is to create a model of human motor-nervous system as complete as possible and able to reproduce gaits affected by Parkinson’s disease. Said work is illustrated by simulation of musculoskeletal human gait controlled by a bio-inspired CPGs based circuitry. We are aiming to create the model consisting of three parts:

- 1) a simulation of basal ganglia decision-making functions that mediate the second part;
- 2) the model of spinal networks of CPGs projecting to muscles through motoneurons;
- 3) a musculoskeletal model of human lower limbs executing locomotor movements and producing exteroceptive and proprioceptive feedbacks.

This abstract presents the two lower parts, their interconnections consisting of 8 CPGs activating 16 muscles on 3 leg joints, and the gaits they can generate.

## II. HUMAN GAIT CONTROL MODELLING

### A. Central Pattern Generators

CPGs are networks of spinal neurons that control rhythmic activities such as muscle contraction during gait. They are able to autonomously produce repeated signals and control muscles with them. Descending signals from brain are not necessary and are used for launching muscle activities and to alternate parameters of CPG.

Our model is mesoscopic multi-pattern CPG. Previously, it was used to generate patterns for humanoid robot

locomotion [2] and more recently for better understanding of robot-human physical interaction like handshake [3].

Initially, our CPG model was inspired by work of Rybak et al. [4] (fig. 1, left) to create bio-inspired rhythm generators from Rowat and Selverston neuron model and apply Hebbian learning rule [5].

Further, CPG model was supplemented with additional sensory neurons and interneuron connections [6]. This resulted in 4 variations of CPG, for each simulated pair of antagonistic muscles. Fig. 1 (on right) shows hip1 variation of CPG model to control Iliopsoas and Glutei muscles. Other variations differ in used receptor feedback and weights of connections.

Set of proprioceptors (comparing to [5]) was expanded to three types of sensory neurons (SN): Ia, Ib, and II. Generally, SN Ia, which react to velocity of muscle contraction, were directed to limit angle and speed of joint. SN Ib react to force produced by muscle and improve sequencing of muscle activation. Lastly, SN II, presented only in flexor muscles, react to muscle length and also help maintaining cycle of gait.

### B. Musculoskeletal Model

To simulate human locomotor system in this work we used “GAIT2DE” developed by Antonie van den Bogert, Orchard Kinetics LLC [6]. It simulates muscle activity and its influence on skeleton to activate legs movements in sagittal plane taking in account internal and external dynamic effects. The human locomotor model used in “GAIT2DE” consists of 7 body segments and 16 muscles (fig. 2). It is implemented as Matlab MEX function.

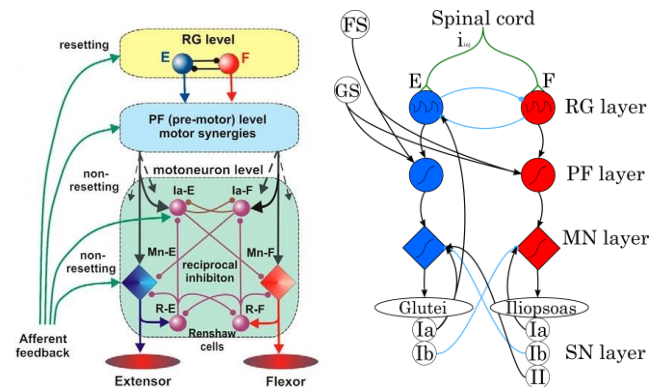


Fig. 1. Left: model of locomotor CPG proposed by Rybak et al. [4]. Right: our three-layer controller, hip1 variation, with connections from [6]. FS and GS stand for equilibrium sensor and ground sensor respectively. RG is rhythm generator, PF is pattern formation, MN is motoneuron, and SN is sensory neuron. E and F stand for extension and flexion half-centers.

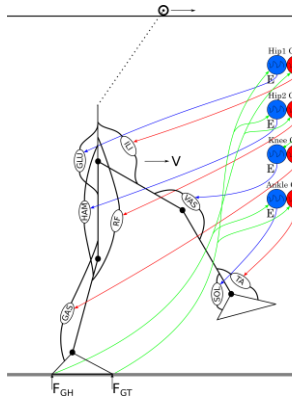


Fig. 2. Structure of Gait2de model, with body segments (trunk, thighs, shanks, and feet), joints (two of each hip, knee, and ankle), muscles for each leg (Iliopsoas (HFL), Glutei, Hamstrings, Rectus femoris, Vasti, Gastroc, Soleus, and Tibialis anterior) [7], their CPGs and connections. V is velocity of pelvis and F are ground reaction forces on heel and toe. Muscles, forces, and CPGs are drawn for one leg.

We modified this model to connect motoneuron outputs of CPGs to each to corresponding muscle (detailed in [5]). Also, we have added ground reaction forces on heel and toe of both legs and to attach a sliding elastic support to help maintain vertical position (dotted line on fig. 2).

### III. RESULTS

This work simulates gait control using 8 CPGs, one for each pair of antagonistic muscles of musculoskeletal model, for example, Iliopsoas and Glutei which turn hip joint in opposite directions. Sensory neurons (SN) of three types: Ia, Ib, and II have different roles in our model. SN Ia react to muscle's velocity of contraction, which is maximal during opposing's motoneuron's (MN) impulse, and don't allow too fast turning velocity. SN Ib react on muscle's instant force. They inhibit opposing motoneurons ensuring order of muscle's stretches. Finally, SN II in our model is present only on flexion side and excites only extension motoneuron (fig. 1, right). They activate while flexor muscle's length is maximal thus keeping the stability of gait.

The resulting model is a dynamic closed-loop controller with physical simulator able to produce stable rhythmic gait in sagittal plane. An important feature of using a CPG as a controller, is its ability to produce repeated patterns without descending signals from brain. This is confirmed in our simulations showing our model of CPG is able to produce stable gait during whole simulation without using input from upper structures.

Fig. 3 shows one gait cycle extracted from our simulations. From the initial standing position of biped model, a stable cycle starts after four seconds of walk. During simulated walk most varied were Ia and Ib proprioceptors, except for hip2 CPGs of both legs. These CPGs innervate Hamstrings and Rectus femoris muscles which affect both hip and knee joints. II sensor had almost the same state during whole gait cycle.

Current set of parameters result in slow stable gait with wide step. Variation of parameters allow to change resulted type, speed of gait and stride length.

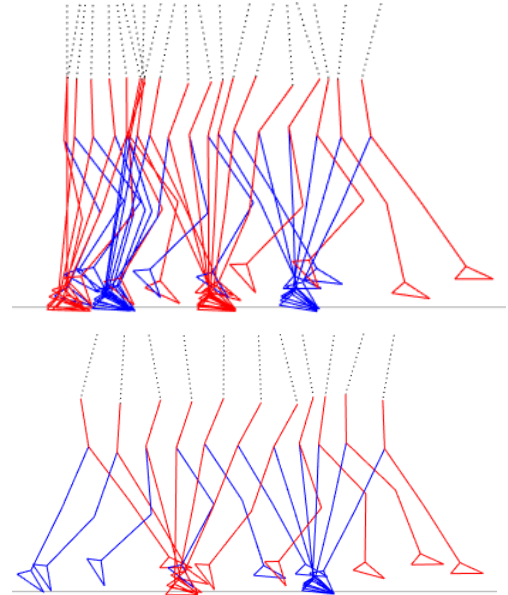


Fig. 3. Above: initial transient gait from standing phase to stable walking. Below: several consecutive frames of further stable gait in Gait2de simulation, time between frames is 0.2 s.

Parameters of each CPG can be varied independently to simulate different types of gait, from slow, narrow steps of parkinsonism; to wide jump-like jogging gait.

### IV. CONCLUSION

This work presents a way to control musculoskeletal gait of human using CPGs. Our controller is able to produce stable gait in sagittal plane using musculoskeletal model with six joints and sixteen muscles. Controller consists of eight CPGs and it uses five types of sensory feedback. Simulation results in Matlab shows that changing intrinsic parameters of CPGs, model produces different types of gait.

Future work is aimed on finding CPG parameters of different types of gait, including abnormal ones. Examples of possible abnormal gaits are limping, ataxic gait, myopathy or parkinsonian gaits, slow, rigid, with freezing of gait.

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