CPG-based circuitry for controlling musculoskeletal model of human locomotor system
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In this paper, a new neuro-musculoskeletal simulator of human locomotor system is presented. This simulator is dedicated to reproduce healthy or altered walking gaits. It contains three joints per leg (hip, knee, ankle) controlled by twelve human muscle models activated by six specific models of central pattern generator (CPG). The CPG consists of three layers and four types of neurons and controls human leg joints. The CPGs are able to generate variable rhythmic signals by changing their intrinsic neural parameters which are controlled by descending signals from mesencephalic locomotor region (MLR), while output signals of motoneurons of CPGs control muscle models. Simulation results in Matlab show that it is possible to generate different stable walking gaits by changing intrinsic parameters of CPGs. According to these changes, the simulator can exhibit coherent or incoherent coordination between the two legs and consequently, stable or unstable walking gaits starting from the double support phase. Results show that this simulator will allow to reproduce walking gaits altered by basal ganglia decision-making system affected by Parkinson’s disease.

Keywords—central pattern generator; human walking; musculoskeletal model; Parkinson’s disease
controlled by network of spinal neurons [6]. They can generate rhythmic activity by themselves. Descending signals from the higher centers are optional, affect the shape of generated patterns, and contribute to the inter- and intra-CPG synchronization.

Current usage research, modelling, and application of CPG vary from investigation of purpose and regimes of specific groups of neurons in different segments of spinal cord [8, 9] through modelling neural networks resembling CPG [10, 11, 12] to synthesis of control units in robotics that have the same behavior patterns of biological CPGs [13, 14].

B. Model of CPG

The model of CPG that was used in this work was proposed and used as a controller for the walk of a humanoid robot [13]. It is based on work of Rybak et al. [10] for a two-level CPG that separates the timing and activation of the locomotion cycle. This model is rather mathematical; however, it is supported by two neurophysiological studies and combines their propositions in multi-layered multi-pattern CPG model.

CPG model is controlled from high-level system (e.g. MLR) that varies the frequency of generated patterns, phase deletion, and clamping of controlling signal. The CPG architecture is composed of three layers (Fig. 1): rhythm-generation neurons (RG); pattern-formation neurons (PF); and motoneurons (MN). Additionally, the model includes feedback sensory neurons (SN) that shape the activity of the CPG neurons.

A neural model of RG neurons was proposed by Rowat and Selverston [12]. It has self-rhythmic generation ability; its oscillation depends on two membrane conductivities for fast and slow current. Depending on these and others cell parameters, RG neurons can generate different patterns: quiescence, almost an plateau, depolarization, and hyperpolarization.

Patterns generated by RG layer are shaped by PF neurons. They also chose the domination rhythm for a joint (flexion/extension). They are capable of rhythm deletion of RG layer without resetting its phase. This means, PF neurons can deactivate motoneurons while RG continue to oscillate. The activation function of PF neurons is sigmoid, whose main parameters are amplitude and saturation.

Motoneurons directly control the muscles with input from PF layer and proprioceptive sensory neurons. Latter measure angle of joint and excite the corresponding motoneuron thus implementing articular reflex. Exteroceptive SN measure foot/ground contact force to excite ankle joint so it steps on full foot. MN and SN also use sigmoid activation function. For detailed mathematical models of cells, refer to [13].

C. Musculoskeletal model

This work uses a modified version of the musculoskeletal simulator Gait2de proposed by Ton van den Bogert [15]. This realistic dynamic model simulates muscle activities (based on Hill model [16]) and their action on skeleton to produce movements in the sagittal plane taking into account physical phenomena (ground friction, forces and dynamics of limbs, etc.). It has nine kinematic degrees of freedom, seven body segments, eight muscles per leg, and its dynamics and outputs are twice differentiable with respect to all inputs. This model is implemented as Matlab MEX function and it takes ~0.03 ms to compute.

Body segments of model are trunk, thigh, shank and foot in each leg. Each of them has the following parameters: mass, length, center of mass, moment of inertia of a human male with body mass 75 kg and body height 1.8 m.

III. NEURO-MUSCULOSKELETAL MODEL

The musculoskeletal model of the human locomotor system proposed in [15] is modified in order to control the muscles by the signals generated by a circuitry based on our model of CPGs.

A. Modifying the musculoskeletal model

As a preliminary work, the musculoskeletal system’s part models six muscles per leg, avoiding the Hamstrings and Rectus muscles that affect two joints at once for easier and more understandable control (Fig 2).

Thus, one CPG control an antagonistic pair of muscles, and CPGs are interconnected together to coordinate the limbs. Forces sensors are implemented on soles to return pressure force on heels and toes to measure the center of pressure. A virtual elastic attached to the top of trunk and able to slide horizontally is added (dotted line on Fig. 2, 4) as lifting support harness like a disabled person. It is implemented as external force F through optional input of the model and is calculated as follows:

\[ F = -k \times (d - L_0) - F_p/2, \]

where k is stiffness of elastic, d distance to attaching point, L_0 testing length of elastic, and F_p is force from last time frame for simulation of elastic’s energy loss.

B. Connecting the CPGs to the muscles

The full scheme of our neural circuitry consists of MLR projection to CPG (Fig 1, 3) as \( \dot{i}_{inj}, \sigma_s, \dot{\alpha}_{MLR}, \) and \( \theta_{MLR} \) parameters. A pulse of \( i_{inj} \) makes CPG to start oscillating and could alter rate of RG [13] if being a sinusoid for example; \( \sigma_s \) is actually a cell parameter, but it can be affected from upper structures (e.g. with neuromodulator or plasticity mechanism); \( \dot{\alpha}_{MLR} \) and \( \theta_{MLR} \) control PF neurons, their coupling to MN and balance between flexion and extension.
Outputs of RG half-centers are connected to PF neurons, which in case of hip simply transform input value range to $[0;1]$, as flexion/extension domination and rhythm deletion through changing $\alpha_{MLR}$ and $\theta_{MLR}$ aren’t applied. PF outputs are connected to MN which excite muscles that rotate hip joint.

The input to musculoskeletal system are neural excitations for each muscle, along with initial state of the model and optional external forces and moments applied to body parts and joints. Each MN provide neural excitations for corresponding muscle [15] that control human locomotor model. Iliopsoas, Vasti, and TibialisAnt are flexion muscles that turn joints counterclockwise (positive direction); Glutei, Gastroc, and Soleus are extension muscles that turn joints clockwise (negative direction).

Additionally, output from MN should be limited to $[0; 1]$ as model does not apply such itself. To close the control loop, CPG contains muscle sensory neurons (SN) for articular reflex that transform angle of corresponding joint into inhibitory influence on each motoneuron. In addition, two ground SN that react to force at contact points under heel and toe and excite MN to help ankle phasing.

IV. RESULTS

A. Walking with constant speed

A distinctive feature of CPG is its ability to produce rhythmic patterns without input like shown on Fig. 4. Figures 5, 6, and 7 show CPG activity, muscle excitations, and joint angles for hip, knee, and ankle respectively.

All joints follow the same connection scheme as on Fig. 1, except that knee CPG’s PF neurons have additional connection (excitatory for flexor and inhibitory for extensor) from hip’s flexor SN that corrects knee phase; and ankle CPG’s PF neurons have two ground sensory neurons (GSN), that reacts to toe ground reaction is connected to flexor PF, heel GSN is connected to extensor PF.

Resulting joint angles are qualitatively similar to human walking cycle [17, 18], especially hip and knee joints that are similar to those in [19], where articular angles of the human hip, knee, and ankle are compared to those with a rigid and non rigid human foot soles.
After change of $\sigma_s$ parameter, model needs about 3 seconds to stabilize its speed showing the global stability of the gait.

V. CONCLUSION

This paper presents a new neuro-musculoskeletal model based on a circuitry of six central pattern generators controlling twelve muscles of the two legs of human locomotor system. Each CPG consists of three layers and four types of neurons. The circuitry is able to generate rhythmic signals controlling the muscles and creating stable walking gaits that can be changed by variation of intrinsic neural parameters. These variations can be controlled by signals coming from an upper level circuitry. Following this way we assume that the neuro-musculoskeletal simulator presented here will be able to simulate impacts of PD disorders on human walking like observed in the medical studies. Though, further work will be aimed at taking into account the Hamstrings and Rectus muscles, simulation of altered walking gaits due to PD, like FoG, based on patients’ data, and at developing a model of nervous links between Basal Ganglia region and this simulator.

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