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Coupling spiking neural networks and mechanical simulations to investigate walking and swimming in salamanders

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1 Introduction

As amphibians, salamanders express a large variety of terrestrial and aquatic locomotor behaviors. In vitro studies showed that the central pattern generators (CPGs) in the salamander spinal cord can generate many of the locomotor patterns observed in vivo [1]. On the other hand, our understanding of the role of sensory feedback during locomotion is limited due to the difficulty of targeting the spinal cord circuits in intact animals. In this context, closed-loop neuromechanical simulations can serve as an important tool to help decipher the organization of the locomotor networks and the role of sensory feedback [1]. In this study we design a spiking neural network (SNN) simulating the locomotor circuits of the salamander's spinal cord. The SNN is linked to a mechanical model that simulates muscles and body properties as well as their interactions with water and ground. The proposed neuromechanical model is capable of generating the coordination patterns associated with swimming and walking trot. The network performance is optimized by means of a multi-objective optimization algorithm, allowing to study the trade-off between locomotion speed and stability of the generated patterns. The proposed model will be used as a neuroscientific tool to investigate the role of sensory feedback during locomotion in intact animals.

2 Methods

2.1 Spiking Neural Network

The SNN consists of a network of adaptive Leaky Integrate and Fire (aLIF) neurons similarly to [2] (see Figure 1A). The network includes populations of reciprocally connected excitatory and inhibitory neurons acting as central pattern generators (CPGs) for the axis and limbs. The CPGs are excited by populations of reticulospinal neurons (RS). The CPGs are also connected to pools of motoneurons (MN), whose spiking activity is low-pass filtered and used as input for the simulated muscle models. The neural network receives sensory feedback from the mechanical model by means of pools of proprioceptive neurons (PS) projecting to the axial and limb networks. The simulation was carried out on Brian2 [3] with an integration step of 1 [ms].

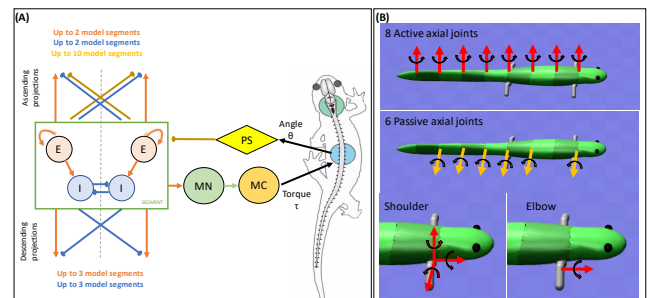


Figure 1: **Neuromechanical model.** (A) The architecture of the neuronal model, comprising excitatory (E), inhibitory (I) and proprioceptive (PS) neurons, motor neurons (MN) and muscle cells (MC). (B) The mechanical model.

2.2 Mechanical Model

The simulated salamander model is 10 [cm] long (see Figure 1B). It contains 14 axial joints and 16 limb joints. Each degree of freedom is controlled by a flexion-extension muscle pair, similarly to [4]. The active component of each muscle is driven by the low-pass filtered neural activities of the flexor and extensor MNs. The simulation was implemented using the Mujoco physics engine [5] through the FARMS simulation framework [6].

2.3 Optimization

In its essence, locomotion serves the purpose of generating a stable motor pattern in order to move fairly quickly from one point to another. The pattern stability is frequently overlooked when modeling the locomotor circuits at high levels of abstraction (e.g. using abstract oscillator models). Conversely, the use of SNN introduces the additional problem of ensuring the rhythmicity of the produced oscillations, which could be disrupted by excessive or insufficient neural signals. In this work, we optimize a salamander model to walk or swim along a straight path. The problem is formulated as

$$\max_p \quad \text{SPEED} \quad (1)$$

$$\max_p \quad < PTCC(M_{F,i} - M_{E,i}) > \quad (2)$$

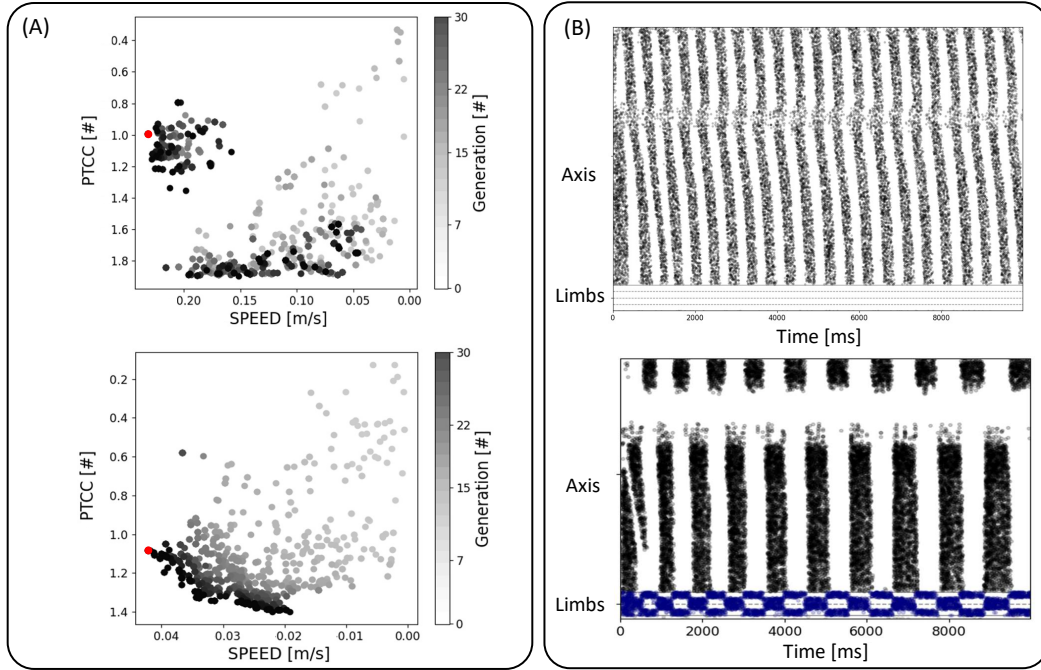


Figure 2: **Optimization and in-vivo-like patterns.** (A) The evolution of the population performance during the optimization of swimming (top) and walking trot (bottom). Red dots represent the fastest solutions. (B) Raster plots showing the patterns of CPG activity for the fastest swimming (top) and trotting (bottom) gaits.

Eqs. (2) and (3) denote the speed and periodicity objectives, respectively. The variable p is the decision vector containing the parameters to be optimized. The stability objective aims at maximizing the peak-to-through correlation coefficient (PTCC) of the motor outputs provided to the mechanical model ($M_{F,i} - M_{E,i}$) and it is a measure of the rhythmicity of the generated neural patterns. The optimization targeted the parameters for the neuromechanical transduction (i.e. the gains for motor output and sensory feedback computation) as well as the drives to the axial and limb RS networks. The total number of optimization parameters was 8 for swimming and 18 for walking. The optimization problem was solved using the Non-dominated Sorting Genetic Algorithm II [7] implemented in Pymoo [8], with a population size of 50 optimized over the course of 30 generations.

3 Results and Conclusions

In Figure 2A, the result of the optimization is shown for walking and swimming patterns. The algorithm returns a set of Pareto optimal solutions that highlight the conflicting relationship between speed and periodicity. In Figure 2B the CPG patterns of the fastest solutions are shown. The obtained activities resemble the ones observed in biological experiments on salamanders [1]. This result shows that, when simulating biologically-realistic SNNs, high speeds can be achieved despite the generation of non-perfectly-periodic patterns. This is likely thanks to the filtering action performed by the physics (i.e. muscles and body). When the optimization is run without the inclusion of proprioceptive feedback similar speed values are achieved but the corre-

sponding oscillations' periodicity is reduced (not shown). This observation suggests that sensory feedback might serve the purpose of stabilizing the ongoing neural activity. The highlighted results pave the way for a systematic analysis of the interplay between open loop and sensory feedback-driven pattern generation in salamanders' locomotion.

4 Acknowledgements

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