A Control Hierarchy Inspired by the Spinal Cord to Exploit Self-Organizing Motion Primitives for Purposeful Trajectory Generation

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Abstract—Inspired by body motion in mammals we propose an embodied control hierarchy for semi-autonomous combination of self-organized motion primitives for goal directed trajectory execution. Movements are adaptive, the setup transferrable to different body morphologies and draws potential for integration in a comprehensive neural network based on Hebbian Learning that behaves similar to neural circuits in the spinal cord.

***Keywords*— Myorobotics, Self-Organization, Hebbian Learning, Spinal Cord, Central Pattern Generator**

1. Introduction

Neural Networks demonstrate great potential for control of musculoskeletal robots with antagonistic control principles. In general, bigger networks naturally lead to more complex behaviors but are very specialized and lack generality. Therefore, in this paper we propose trajectory execution based on two phases of self-organized motion primitive generation and its following combination to new behaviors. Inspiration is drawn by pattern generators in the Spinal Cord but in contrast to Central Pattern Generators we exploit self-organization for behavior generation to remain generality and adaptability.

On the example of a tendon-driven Myorobotics shoulder arm imitating a musculoskeletal biological body we demonstrate semi-autonomous execution of trajectories.

Our results may contribute to a better understanding of motion execution by neural circuits in the spinal cord but as well build a base for small neural networks that can efficiently generate and execute motions with biomimetic robots.

2. Musculoskeletal Robot and Self-Organized Behavior Generation

As a test environment we utilize a Myorobotics robot that mimics a human shoulder arm. A ball and socket shoulder and revolute elbow arm are controlled by antagonistically arranged tendon-driven actuators. The Myorobotics muscle units imitate muscle fibers: A tendon is rolled up while a series elastic element includes flexibility. Sensor feedback is provided in terms of force, position and velocity according to muscle afferents.

For generation of motion primitives, the Differential Extrinsic Plasticity (DEP) learning rule as introduced by Der and Martius [1] is exploited. A single layer feed forward neural network with

$$y_i = tanh(\sum_{j=1}^{n} \kappa \gamma_i C_{ij} x_j + h_i)$$

maps sensory information x (force + position) to muscle motor control commands y. An incorrect inverted model of the world with a modelling error dy serves as learning basis for explorative behaviors and sensory input is delayed for periodic pattern generation. In [1] the DEP rule has been applied to the Myorobotics arm and demonstrated generation of a variety of self-organized periodic arm motions that are adaptive to environment interactions.

3. Proposed Control Components and Hierarchy

Experiments with decerebrated cats show that body motion patterns can be recalled by inducing electrical

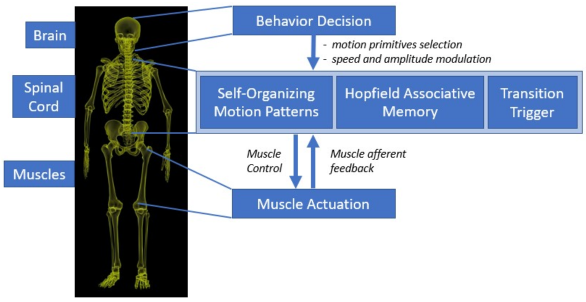

Figure 1: A Control Hierarchy inspired by motion execution in the Spinal Cord

stimuli in the mammal's brainstem [2]. Analogous, in our setup user input (behavior decision) specifies a desired motion pattern to be executed as well as its speed and amplitude. Figure 1 depicts our proposed control hierarchy that imitates functionalities of the brain, spine and muscles. The central components of the spinal cord for periodic motion generation and storage are based on Hebbian Learning, a simple neural network triggers subsequent motion patterns:

- **Behavior Generation**: A rate based neural network applying the DEP learning rule in a closed-loop of the sensory motor map of the musculoskeletal robot arm
- **Behavior Storage**: The weight matrices of the neural network representing the different motion patterns are stored in a Hopfield network and are recalled associatively by motion selection commands
- **Motion Trigger**: A two-layer neural network as shown in figure 2 detects potential transition points and triggers a

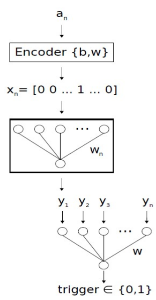

Figure 2: Two layer neural network for transition triggering based on motor poses a_i

transition to the following motion pattern autonomously after its specification. For this purpose motor positions are continuously encoded as Sparse Distributed Representation and experimentally specified transition points are stored in the network weights.

In a first learning phase self-organized motion primitives are generated by manual interaction with the robotic arm and stored as weight matrices, as well the trigger network is initialized accordingly. Afterwards a desired trajectory can be generated by sequential input of the underlaying motion primitives, the speed and frequency can be adapted continuously.

4. Results

We generated three different periodic motion primitives as visualized in the principle drawing of figure 3 to cover the cartesian motion space of the robots forearm. All motions can be modelled in terms of frequency (about 0.25 Hz to 0.8 Hz) and amplitude (about 2 to 6 radiants motor position). We identify reasonable transition points in the pattern centers and adjust the trigger network accordingly (blue). The red line indicates a potential generated trajectory assembled out of various motion primitive parts: a subsequent motion primitive can be selected at any time since the system autonomously transitions whenever a transition point is reached. Weight matrices can be recalled associatively from the Hopfield network, whereas improvements for storage capacity need to be addressed prospectively. The transition quality is improved by providing modelled context information assuming a perfect subsequent motion primitive instead of the actual history context. Figure 4 demonstrates an example result of switching between two stored motion primitives combining quarter patterns each. The transitions are stable and free of disturbances, the top shoulder muscle (yellow) not affected by a change of direction transitions smoothly.

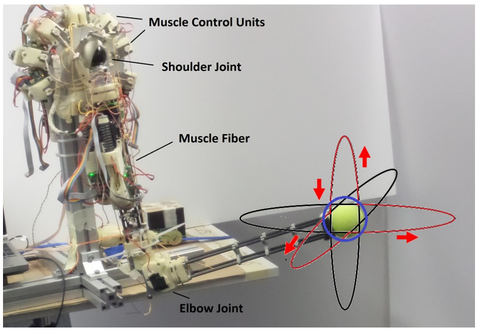

Figure 3: Schematic drawing of trajectory execution based on basic motion primitives on the Myorobotics tendon-driven shoulder arm: A goal directed motion is executed by combining parts of previously self-organized motion primitives whereas the motion transition itself is triggered autonomously by a simple neural network.

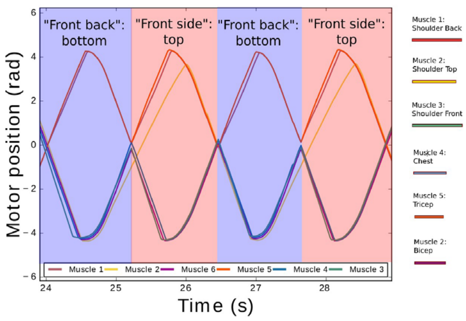

Figure 4: Motor position plots for five shoulder muscles demonstrating fluent transitions without disturbances and loss of motion amplitude.

5. Conclusion

In the demonstrated experiment setup we can generate purposeful trajectories as a combination of self-organized motion primitives. Hereby, speed and amplitude can be varied while a triggering mechanism autonomously transitions to the next selected motion primitive.

The proposed approach of using motion primitives as building blocks for complex behaviors is very similar to current implementations with Central Pattern Generators as e.g. in [3]. However, in our implementation the patterns itself are self-organized so that motions evolve self-explorative based on the body morphology and remain highly adaptable to any disturbance.

Two aspects let the proposed approach compare to biology: The neural circuity in the spinal cord is build up of not more than five layers, in our setup we only utilize networks with a maximum of two layers. Furthermore, plasticity in the spinal cord decreases with development time. With our setup we propose a phase of learning motion primitives that afterwards are combined to achieve fast execution of desired trajectories in the full action space.

Since most components are based on Hebbian Learning Rules, future research will move towards a single comprehensive associative network that generates, stores and triggers motion patterns. To further compare the results with biological findings the Neurorobotics Platform [3] will be exploited to set up a closed loop control simulation experiment with musculoskeletal human and animal models.

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References

[1] Der, Ralf, Martius, Georg. (2016) "The World as its own best controller: A case Study with anthropomimetic robots", CoRR vol. abs/1602.02990

[2] C. T. Liverman, B. M. Altevogt, J. E. Joy, and R. T. Johnson, *Spinal Cord Injury: Progress, Promise, and Priorities*. Washington, DC: The National Academies Press 2005, p. 51, isbn: 9780309095853. doi: 10.17226/11253

[3] C. P. Santos and V. Matos, "Gait transition and modulation in a quadruped robot: A brainstem-like modulation approach," *Robotics and Autonomous Systems*, vol. 59, no. 9, pp. 620–634, 2011, issn: 09218890. doi: 10.1016/j.robot.2011.05.003.

[4] Albanese, Ugo, Sharma, Kenny, Feldotto, Benedikt, Akl, Mahmoud, Weber, Sandro, Mahmud, Hossain, … Gewaltig, Marc-Oliver. (2018, May 31). HBP Neurorobotics Platform (Version 2.0). Zenodo. http://doi.org/10.5281/zenodo.1296203