

**A computational biologically inspired model of motor control of
direction**

A thesis presented

by

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Abstract

Sensorimotor coordination has been an active research topic for both neuroscience and artificial intelligence over the last decade. For the visual guidance of movement to be efficiently implemented in artificial systems, it is essential to understand the computational mechanisms underpinning biological motor control. This thesis explores the development of visuomotor coordination within a biologically inspired computational framework based on spike-processing neural networks.

Firstly, we address the development in a self-organizing map of neural directional selectivity. As a result of the learning process and of the input patterns used, the network develops a distributed representation of 12 directions of movement. The population code resulted is analyzed using the population vector scheme and is compared with neurobiological data on motor cortex organization.

Secondly, we propose a computational mechanism based on spike-timing dependent learning, for the transfer of directional information between a visual and a motor map. Learning of the visuomotor mapping resides in the development of connection strengths that are dependent on the similarity between the preferred directions of neurons in the two maps. The computational mechanism and the neural behaviors resulted are discussed with respect to their neurophysiological implications. We believe that biologically inspired modeling of motor control development can be highly beneficial to the understanding of brain computations underlying movement control.

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Dedicated to my parents

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