A hierarchical, neural-dynamic architecture generating sequences of timed movements

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Humans excel at racket sports and ball games where it is crucial to coordinate multiple actions in time, and adapt those movements online to a quickly changing environment. To return a tennis serve, for instance, a player has to produce a whole set of actions: tracking the ball, predicting its trajectory, initiating a timed movement to hit the ball, estimating movement parameters, and updating them during the movement according to changing sensory information. Finally, once the ball is hit, the player will have to get into a good position, in anticipation of the next incoming ball. Now the same behaviors will have to reused, but in a different context and with different movement parameters.

Emulating these human skills in robots remains a vast challenge. Robotic solutions proposed for hitting or catching balls (see e.g., [4]) often rely on fast and accurate algorithms that fail to adapt online to changes in sensory information. Other approaches use movement primitives learned from human demonstrations [3]. Although able to adapt to a changing environment, they are often unable to generate flexible sequences of movements.

We propose a model that autonomously generates flexible sequences of timed movements. The timing of the movements is controlled by non-linear oscillators. Their activation and deactivation is organized by a hierarchical neural-dynamic architecture. We demonstrate the features of our model in an exemplary robotic application where a robotic arm continuously hits a ball up an inclined plane.

Our model is based on Dynamic Field Theory (DFT) [6], a mathematical framework for cognition. In particular, we build upon a framework for behavioral organization that we have previously introduced in a grasping task [5]. Within this framework, complex tasks are subdivided into *elementary behaviors* (EBs). In our model, EBs are organized into two hierarchical levels [1], representing different levels of abstraction. Elementary behaviors on the higher, more abstract level represent timed movements (e.g., moving the arm toward the ball) and control *movement modules* on the lower level. A movement module is concerned with controlling a specific part of the movement (e.g., the movement of the arm along a single axis). It consists of the following sequence of EBs (1) memorize the current state before starting a movement (2) initiate the timed movement toward a target location by switching the dynamics to an oscillatory regime (3) stabilize the end-effector at a postural state after executing the movement

The autonomous generation of movement sequences is tightly coupled to visual sensory information about the ball motion and able to adapt on-line to perturbations introduced in the ball trajectory. The movements sequencing rules are encoded by perceptual and task specific constraints and controlled by perceptual information about the ball. All parts of the system are connected by tunable synaptic weights, making the system open for learning. The concept of EBs have previously been successfully combined with the principles of reinforcement learning, learning sequences of behaviors that lead to a reward [2].

We evaluated the core properties of the proposed model both in a physically realistic Matlab simulation and in a hardware implementation. The results illustrate how the system is able to react appropriately in response to external perturbations on the ball by initiating, aborting, or re-initiating inactive behaviors at any time. Furthermore, the system may also update movement parameters such as the amplitude and movement time on the fly when such perturbations shift the timing and spatial constraints.

References

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