The Role of the Sensorimotor Loop for Cognition

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***Abstract*—Locomotion is most of the time considered to be the result of top-down control commands produced by the nervous system in response to inputs received via sensory organs from the environment. Locomotion may arise alternatively when attracting states are stabilized in the combined dynamical space made up by the brain, the body and the environment. Cognition is embodied in this case within the sensorimotor loop, viz self-organized. Using a physics simulation environment we show that self-organized locomotion may result in complex phase spaces which include limit cycle corresponding to regular movements and both strong and partially predictable chaos describing explorative behavior.**

I. Introduction

We used the LPZRobots physics simulation environment [1] to investigate the occurrence of self-organized embodiment in robots for which sensation is confined to propio-sensation. The 'brain' of the robot, consisting of a single controlling neuron per actuator, receives sensory information only regarding the actual position $x_i^{(a)}$ of the actuators $i = 1, 2, 3$, which are in turn translated via

$$x_i^{(t)} = R\left[2y(x_i) - 1\right] , \tag{1}$$

to a target position $x_i^{(t)}$ for the i-th actuator (compare Fig. 1). R denotes here the (rescaled) radius of the spherical robot and $y(x_i) = 1/(1 + \exp(-x_i))$ the firing rate of the controlling neuron. The membrane potential x_i is determined via

$$\dot{x}_i = -\Gamma x_i + \frac{w_0}{2R}\left(x_i^{(a)} + R\right) - z_0 \sum_{j\neq i} u_j \varphi_j y(x_j) \tag{2}$$

by the relaxation constant Γ, by the coupling $w_0 > 0$ to the proprio-sensory reading of $x_i^{(a)}$, and with $(-z_0) < 0$ by the inhibition it receives from the other two neurons. The interneural inhibition is dynamically modulated presynaptically by a mechanism known as short-term synaptic plasticity (STSP) [2], which we model as [3]:

$$\begin{array}{rclcrcl} \dot{u} & = & \frac{U(y)-u}{T_u} & \quad & U(y) & = & 1 + (U_{\max} - 1)y \\ \dot{\varphi} & = & \frac{\Phi(u,y)-\varphi}{T_\varphi} & \quad & \Phi(u, y) & = & 1 - \frac{uy}{U_{\max}} \, . \end{array}$$

Both the effective Ca^{2+} concentration u and the fraction of available vesicles φ of neurotransmitters relax to unity in the absence of a presynaptic input y, which, when present, tends to increase/decrease $u \to U_{\max}$ and $\varphi \to 0$ respectively.

We note that STSP is well known to change synaptic efficiencies transiently by up-to fifty percent on time scales of a few hundred milliseconds, as defined by T_u and T_φ. These are also the time scales which are relevant for locomotion. STSP does not induce any long-lasting traces (modifications of the synaptic strength), being hence a fully transient form of plasticity which tends to destablize fixpoint attractors.

II. Autonomous mode switching

The here considered robot moves only, as an entity comprised of body and controlling neurons, when embedded within the environment. Locomotion corresponds then to self-stabilizing attractors in the combined phase space of the controlling neural network, of the body and of the environmental degrees of freedom it couples to [4].

Our robot may engage in a rich palette of regular motion patterns, as illustrated in Fig. 2, which are stable either for distinct sets of internal parameters, such as the bare synaptic weights w_0 and z_0, or simultaneously. Autonomous mode switching corresponding to a rollover from one to another basin of attraction occurs regularly in the latter case upon collision with either an external object, or with another robot. We note, importantly, that limit-cycles corresponding to regular motion, as shown in Fig. 2, are continuously degenerate with respect to the direction and/or to the center of propagation.

III. Explorative Chaos

Explorative behavior arises when the synaptic weights w_0 and z_0 are set such that chaotic attractors are formed within the

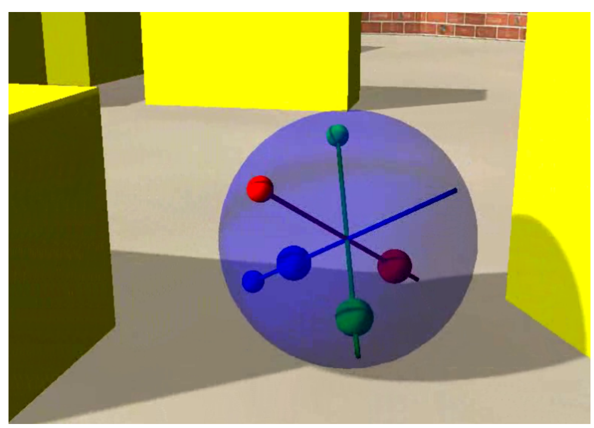

Fig. 1. The simulated robot contains three weights (red, green and blue) moving along perpendicular rods within a movable sphere. The position of the three weights is controlled respectively by a single neuron (see Eqs. (1) and (2)). The small balls at the end of the respective rods are guides to the eye. [video]

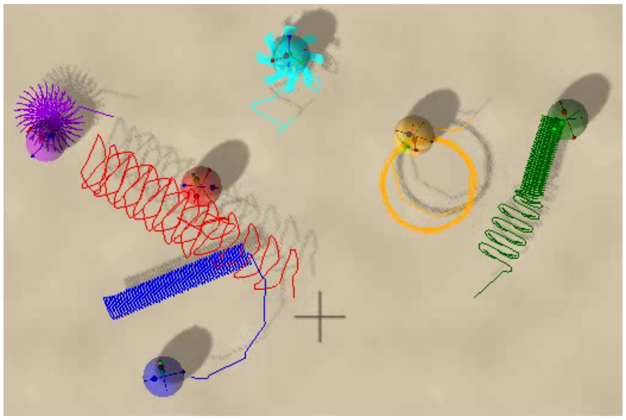

Fig. 2. Six color-coded copies of the sphere robot starting each with slightly different synaptic weights w_0 and z_0. The pink, cyan and yellow robots perform various types of circular and star-like motions, with the red, blue and green robots staring to move with finite translational velocities. For the parameters of the blue and of the green robot two limit cycles coexist. Both robots undergo collisions (the blue colliding with the red robot and the green with the yellow robot), which induce transitions from one to the other attracting state. A previous collision of the red with the pink robot resulted (just) in a direction reversal. [video]

sensorimotor loop. We note that noise is absent for the simulations shown in Fig. 3, with the seemingly random wandering of the robot resulting exclusively from the chaotic nature of the underlying attractor. Two types of chaotic attractors may be stabilized in addition, denoted respectively as strong and as partially predictable chaos [5].

IV. Playful locomotion

Morphological computation [6], [7], [8] may occur when the body plays a central role in cognition. For a test of this concept we have situated the sphere robot in a structured environment, as shown in Fig. 4, containing movable blocks. One observes that our three-neuron robot starts to engage in

Fig. 3. Two color-coded copies of the sphere robot exploring a maze. The motions can be classified as strongly chaotic for the cyan robot and as partially predictable chaos for the blue robot [5]. The blue robot switches to another locomotion mode after colliding with the wall. The resulting radius of the circular mode is, however, too large for the maze and it can follow it hence only transiently. [video]

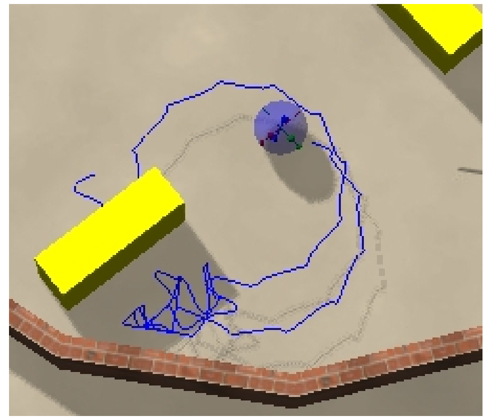

Fig. 4. Within a structured environment the robot starts to push blocks around in a seemingly 'playful' manner. [video]

a seemingly ‘playful’ manner with its environment, pushing blocks around by bumping into individual objects repeatedly. This occurs, from a dynamical systems point of view, when the robot switches upon collisions back and forth between stable chaotic motion and another weakly unstable, or alternatively as in Fig. 3, stable coexisting limit-cycle attractor describing regular locomotion.

V. Conclusion

The sphere robot does neither perform any form of knowledge acquisition with its brain consisting of only three neurons, nor does its ‘cognitive system’ dispose of higher-level internal drives or motivations. The explorative behavior observed in Figs. 3 and 4 can be explained on the contrary fully in terms of dynamical systems theory. Taking a philosophical perspective our simulated robots hence demonstrate that it is in general impossible for an external observer to deduce reliably the internal settings and motivations of an acting cognitive system.

References

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