

flow fields, and turbulence. Even if the structural accuracy of the airplane to model target behavior (that of the bird) was developed further – in the sense that if the airplane could flap its wings, land with soft collisions, and so on, – it is unlikely that much more would be identified about the neurophysiology or the behavioral organizational principles of bird flight.

Even though the biorobotic control systems mentioned by Webb are a significant improvement over the classic cybernetic models, they still make assumptions similar to the cybernetic approach. To illustrate this, let us consider the example of the simplest control system, the thermostat. Temperature regulation is achieved in the thermostat by minimizing the difference between the actual temperature of the room and that of the set point. The set point is prescribed by an external source and is not specified by the system itself. In contrast, biological control systems have the capacity to internally modify the set points of different subsystems and thus intentionally initiate the transition from one steady state to another, a dynamical process underlying voluntary actions (Feldman & Levin 1995). For example, the human arm as controlled by the nervous system can reach desired positions by prescribing a set point, which is achieved by active engagement with the environment, gravity, inertial, and reactive forces. Muscle activation patterns, forces, torques, and trajectories are not programmed or computed but are largely emergent in biological systems in the process of interaction with the environment. Whereas, even in the most sophisticated examples used by Webb, such as modern robotic approaches called force control models (Wolpert et al. 1998), these variables are directly programmed and computed. The dynamical mechanism of state resetting is largely ignored, simply because the computational principles underlying imitations of biological movements in robotics conflict with the natural, dynamical nature of the resetting mechanism underlying intentional movements.

To emphasize this point, consider the posture-movement problem in biological control of movement as formulated by Von Holst and Mittelstaedt (1950/1973). He noticed that there are powerful neuromuscular mechanisms (“postural reflexes”) that generate electromyographic (EMG) activity and forces in order to resist perturbations that deflect the body from an initial posture. At the same time, it is clear that the organism can intentionally adopt different postures. Each new posture adopted by the system might be considered as a deflection from the initial one. The deflection would result in resistance tending to return the system to its initial position. How then is an intentional movement from the initial posture and the achievement of a new posture of the body possible without resistance? It has been established that the nervous system can reset the postural state by changing length-dimensional parameters – muscle activation thresholds (Asatryan & Feldman 1965; Feldman & Orlovsky 1972; Matthews 1959). By resetting these thresholds, the system shifts the spatial coordinates at which an equilibrium posture can be reached and maintained. Thereby, the initial posture appears to be a deflection from the newly specified posture. Therefore, the same neuromuscular mechanisms that produce EMG signals and forces in response to deflections from the initial position produce, without any programming, EMG signals and forces tending to eliminate the deflection from the new posture and thus move the system to it (Feldman & Levin 1995; St-Onge et al. 1997). This postural resetting mechanism was also confirmed by the finding that many systems, including cortico-spinal descending ones, have the capacity to regulate the activation thresholds. Further support stems from recent studies showing dramatic movement problems following deficits in the regulation of activation thresholds in neurological patients (Levin & Dimov 1997).

Stemming from robotics, force control models fail to answer the basic question posed by Von Holst and Mittelstaedt (1950) on how the system can actively move from an initial posture without triggering resistance. By disregarding the empirical mechanism of postural resetting (shifts in muscle activation thresholds), force control models produce movements by overcoming such resis-

tance. For example, Schweighofer et al. (1998) simulated planar point-to-point arm movements using a force control strategy. Their equations show that after the movement offset, muscles generate tonic activity in proportion to the distance between the initial and the final muscle lengths. This implies that the final position is reached by overcoming the resistance to the deflection of the arm from the initial position. Thereby, at the final position, the muscle activity cannot be minimized without driving the limb back to the initial position. This prediction of the force control strategy obviously conflicts with the common observation that after transition of the arm to a new position, muscle activation can be minimized without arm motion. Control strategies that tolerate the resistance to deflections from the initial posture each time when an active movement is produced are highly inefficient in terms of energy costs. Incorporating the empirically established mechanism of postural resetting in a motor control theory comes with a price: the resetting mechanism implies that output, mechanical variables do not need to be directly programmed or computed to make adequate actions. This implication conflicts with the basic, computational principles underlying force control models and thus questions their physiological feasibility, despite their efficiency in robotics.

We conclude that while great strides have been made in biorobotics, there is still a long way to go before robotics can make pertinent contributions to biology. The contributions of biorobotics to biology can be greatly accelerated if engineering approaches take into account the context in which biological systems generate solutions to real world problems.

From reflex to planning: Multimodal versatile complex systems in biorobotics

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Abstract: As models of living beings acting in a real world biorobots undergo an accelerated “phylogenetic” complexification. The first efficient robots performed simple animal behaviours (e.g., those of ants, crickets) and later on isolated elementary behaviours of complex beings. The increasing complexity of the tasks robots are dedicated to is matched by an increasing complexity and versatility of the architectures now supporting conditioning or even elementary planning.

The edge of biorobotics over plain mathematical modelling.

Robotic models result from a back-and-forth interaction between mathematical models’ simulation in “gedanken” experiments, and robotic models’ experiments in the real world. As such, they do not constitute a different type of, but actually a step further to, classical modelling.

From our experience of complex systems, a few points are emphasized. First, a complete behaving system, as in a robotic model, requires a necessary “horizontal” mechanistic integration, at the basic level of network interactions between different components of the global architecture (sensory, motor, associative, timing, planning, and so on), that enforces self-consistency among coordinated systems (at variance with the “vertical” integration between different levels of explanation alluded to in the target article). This “horizontal” integration is rarely achieved in network modelling characterized by a tendency to build dedicated architectures for specific tasks without caring about their functional integration in a system. Less accuracy or some degree of approximation is the price to pay. The specific import of biorobotics in the “vertical” integration has been to stress the interdependence be-

tween agent morphology and control system, and to provide a test of congruence between the model of the agent and the model of its environment thanks to dynamic interactions with the external world during robotic experiments.

Second, model-grounding in the real world by compliance with physical laws (such as spatio-temporal continuity, gravity, and so on) is a lever to the system's simplification rather than a constraint. Learning a real environment (during an individual lifespan or a species' evolutionary period) is paradoxically a source of simplification in this type of solution and solution-space dimensionality. Combinatorial explosion of the solution domain is prevented by probabilistic sorting out of the situations actually encountered in the real world. As illustrations from our model: (1) Assuming spatio-temporal continuity expressed by the formalism of neural fields (Schoener et al. 1995) allows stable target selection and smooth, robust control. (2) Control architectures can take advantage of inherent perceptual ambiguity to perform complex tasks in a simple way, with disambiguation resulting from the dynamics of the behavior. (3) Sensory and motor modules designed in compatible or similar coordinate systems achieve a great simplification of the information flows (Gaussier et al. 1999).

Third, two dimensions of neural organisation, relevant for humans as well as robots, account respectively for the nature of the functions performed (e.g., spatio-temporal processing and navigation, linguistic processing, episodic learning), and the level of performance (reflex, conditioning, planning). The first horizontal dimension specifies, according to combined perceptuo-motor modalities, the nature of the parallel processes performed, whatever their level of performance. It depends on the combination of the multimodal associations (e.g., visual [exteroceptive] and movement related [interoceptive] inputs in the computation of

space during navigation; auditory but also visual inputs in speech and language processing; and so on). Each peculiar combination of associations specifies a function. The second vertical dimension specifies the level of performance (stimulus-response reflex behaviour, conditioned automatic behaviour, planned controlled behaviour), whatever the nature of the functions involved. This second sequential, or rather, iterative aspect unfolds in cortico-subcortical loops characterized by the dual process of convergence-contraction and divergence-expansion of information, and gives rise to different levels of pattern-recognition (uni- or multi-modal events, transitions, chunks, sequences, plans).

Illustration by a generic spatio-temporal control system. Depending on these two dimensions, dedicated architectures can become generic and, as such, used for multiple implementations according to the input-output nature and the level of processing. We assumed common mechanisms for spatio-temporal processing during navigation and declarative-episodic memory. Both depend on spatio-temporal sequence learning based on a cascade of associations and pattern recognition performed in cortico-hippocampal loops.

The computational model implemented as a robot control system features three levels of organization (Fig. 1a) linked by intrahippocampal and cortico-hippocampal loops. First, a basic hippocampal level learns events (whatever their nature, e.g., places), transitions between events, and chunks. Second, the intermediate level links sensory information to motor responses in relation with drives and reinforcement. Finally, the cortical level links and stores sequences of chunks to form graphs and maps that can be used for planning in relation with goals and motivations. According to the nature of the input-output modalities, the system can be used to learn timing and temporal sequences, motor sequences for

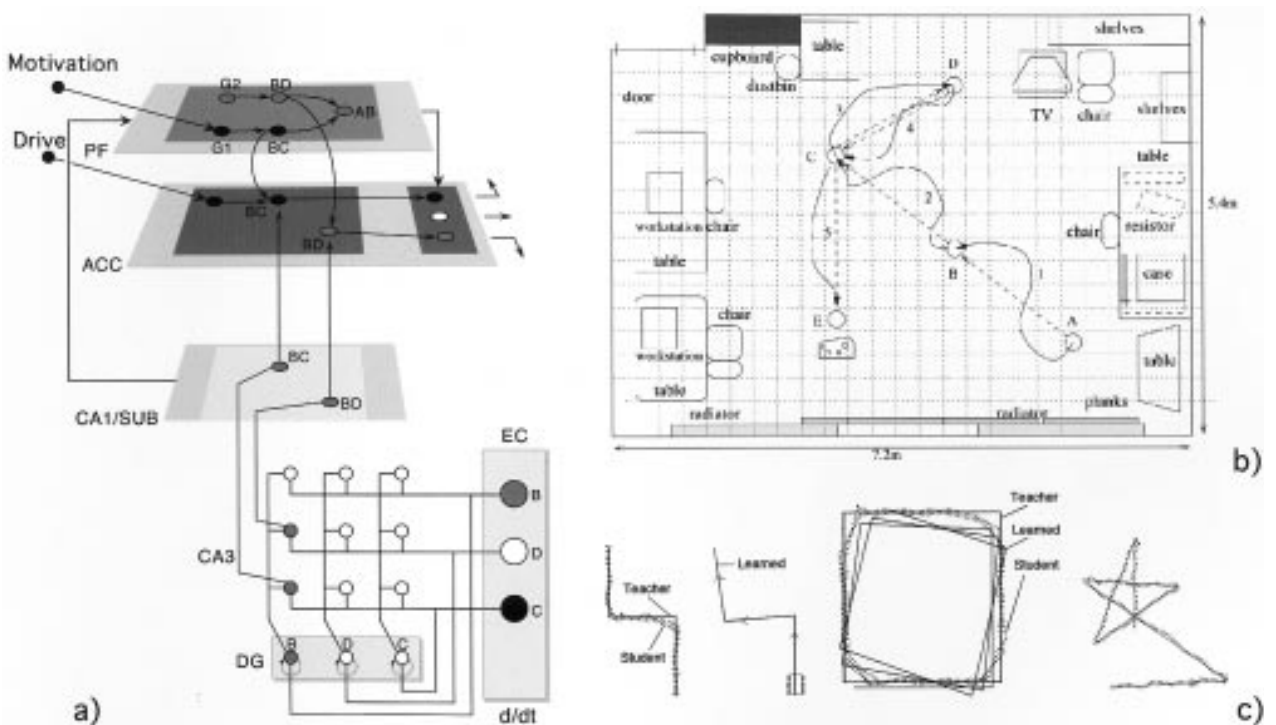


Figure 1 (Banquet et al.). (a) Three-level generic architecture featuring hippocampus (EC, entorhinal cortex; DG, dentate gyrus; CA3-CA1; SUB, subiculum), intermediate level of basal ganglia (ACC, accumbens), and cortex (PF, prefrontal). (b) Learning of places (A,B,C,D,E), transitions, and associated trajectories while exploring an indoor environment. (c) Imitation and learning of the teacher trajectories by a student.

imitation, or temporo-spatial sequences for navigation (Banquet et al. 2001).

In our model of timing and sequence learning, cell populations with different time constants extend an event-related phasic signal for different delays (so learning the timing between two events). The transition between two successive events, thus made co-occurrent, is learned by a hetero-associative network (Banquet et al. 1997; 1998). In one trial, event-transitions and temporal sequences are learned, as for a melody.

The same basic architecture, complemented with a sensorimotor module that feedbacks proprioceptive inputs to the hippocampal system performs protoimitations (Gaussier et al. 1998) and learns arbitrary trajectories (Fig. 1c). The system, based on a homeostasis principle, minimizes the difference between teacher-movement perception and student movement. Structuring the movements of the teacher in movement-transitions allows online imitations and learning of the imitated sequences. A playful version of this robot model (imitating vs. being imitated) is implemented as an aid to understanding autistic behaviour whose main handicap results from a deficit in social interactions (Andry et al. 2001).

The same architecture (Fig. 1a), when receiving visuo-spatial inputs, learns not only transitions between places during the exploration of an environment, but also (thanks to path-integration) the ideal trajectory between two places, and associates this trajectory with the transition (Fig. 1b). Learning can either be latent (Hebbian without reinforcement) or reinforced (higher order conditioning) by a reward. Yet, transition-learning, combined with the propagation along the graph of the activation initiated by goal representation and motivation (Fig. 1a), allows discovering transitions never experienced before, and managing several simultaneously active goals (Gaussier et al. 2001), according to their salience.

The biorobotic models certainly do not constitute a proof of the existence of similar neurobiological mechanisms, but rather, a guarantee of functional realism and plausibility, and a questioning tool capable of suggesting unexpected hypotheses on biological systems.

Models of complexity: The example of emotions

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Abstract: Using the example of the difficulties which emerge when trying to model complex behaviors – such as emotional expression – that result from stochastic interactions between different components, we argue that biorobotics may well describe one possible evolution of certain features of a biological system, but cannot pretend to be a simulation of the whole behavior of the system.

Robots are believed to mimic the behavior of biological systems, but do they model complex behaviors, such as emotional expression? Several robots have been built that include the so-called “emotional model.” For example, the AIBOT, which is a home entertainment robot simulating a dog’s behavior, seems able to express “emotional behavior” (Pransky 2001), while human head-like robots can communicate with humans by changing facial color expression (Miwa et al. 2001a). The major reason for including such abilities may be to advance the sociability of the robots; emotional models facilitate communication between robots and humans (Miwa et al. 2001a) and machines carrying them are so much more attractive (Ogata & Shigeki 2000). Other reasons for in-

cluding “emotional models” could be to facilitate adaptation to natural and unpredictable environments (autonomy of the system), and to improve cognitive processes. Indeed, it has been suggested that emotions may be a process crucial for cognition (Chevalley & Belzung 2001). In fact, there is substantial evidence indicating that emotions may be mediators between low-level reactive behaviors and high-level rational behaviors. What kind of model do these “emotional systems” use? The human head-like robots use the so-called “equation of emotion” (Miwa et al. 2001b) which consists of the following process: (1) the robot senses the stimulus (Miwa et al. 2001a); (2) the robot appraises the stimulus according to three dimensions (pleasantness, activation level, certainty); (3) the robot generates a “mental state” using an equation (called “the equation of emotions”) integrating the three dimensions; (4) it loads the response, which can consist of a modification of its facial color by using red EL (electroluminescent) sheets. Other models are based upon the imitation of the human endocrine system to adjust various internal conditions such as motor output or sensor gain (Ogata & Shigeki 2000).

So, the models used are based upon the production of a serial linear process, occurring at the psychological or the physiological levels. This is quite a simplistic modeling, because in biological systems emotional expression may in fact result from complex interactions between different causes, including ones related to the natural history of the species (genetic factors) or to the events the subject has been faced with (epigenetic factors), to psychological states, to brain circuitry, neurotransmitter systems, and so on. Each of these factors participates in the generation of emotions by activating a complex set of parallel distributed processes (Chevalley & Belzung 2001), which permanently interact with all the others so as to yield an unpredictable response. Therefore, there may be some elements of the behavior of biological models which cannot be simulated in robots. Furthermore, it is rather probable that even though robots may imitate some aspects of the emotional expression (such as changes in face color), they cannot have an emotional feeling. This further emphasizes how impossible it is to mimic emotional behavior.

The case of emotions well exhibits the difficulties we face when attempting to model human behavior. But it also exhibits the ambiguities of our conceptions of what modeling is. The methodological approach that was associated with modeling at the time of a crisis in the fundamental concepts of Mechanics in the 1880s was a very sophisticated one. Heinrich Hertz (1894/1956) was the first to use the word “model” in connection with a new conception of the “theory of knowledge” (see, notably, his definition of what is a “dynamical model” in Bk. II, sect. 418), and this inspired people as different as Boltzmann, Wittgenstein, Cassirer, Bohr, and Heisenberg. Assuming that a model is a representation that is a construct of the mind and may have no resemblance whatsoever to the thing it represents, Hertz based his epistemology of the *Scheimbilder* on the idea that the agreement between Mind and Nature can be compared to the agreement between two systems one of which is a model of the other. There must exist between the two something like what Helmholtz (1878/1921) had called “parallelism in law-likeness”: namely, there must be a strict correlation, not between the system modeled and its model, but between the law of *evolution* of the system modeled and the law of *evolution* of the model. Among other motivations, such as introducing “hidden masses” in the science of Mechanics, this was meant at the time as an argument against all naïve “pre-Kantian” conceptions of knowledge based on the notion of a resemblance between things and ideas, or between systems and their symbolic expression. To Hertz, the benefit of modeling was to allow us to focus not on objects, but on law-likeness (*Gesetzlichkeit*).

From the beginning, then, a model was different from a simulation. This is the background of Bohr’s claim that a representation of the atom could not in any way “look like” the planetary system, while it should account for the discontinuities observed in experimenting on radiation phenomena. Building a model is not simulating a process, rather, it is building one possible interpreta-