Biorobots, nonlinear dynamics and Perception

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Abstract. In this contribution a survey on a novel approach to locomotion and perception in biologically inspired robots is presented. The basic electronic architecture for modeling and implementing nonlinear dynamics involved in motion and perceptual control of the robot is the Cellular nonlinear network paradigm. It is shown how this continuous time lattice of neural-like circuits can generate suitable and real-time dynamics for efficient control of multi-actuators moving machines, and also to create the basis for a perceptual control of their behaviors.

Introduction

The challenge to conceive, design and build neuro-inspired machines, requires a deep scan into different disciplines, including Neuroscience, Artificial Intelligence, Biorobotics, Dynamical Systems Theory and Electronics. New types of moving machines should be more closely related to biological rules, not discarding real implementation issues. The recipe has to include neurobiological paradigms as well as behavioral aspects from one hand, and new circuit paradigms from the other hand. These latter should be capable of controlling in real time robots with an ever increasing level of autonomy, adaptability and intelligence.

In addition, Biorobotics has a lot to share with Biomimetics[1-2], i.e. with the design of machines mimicking the structural aspects of animals. In our view, a biorobot, like the inspiring living being, is a Complex System, i.e. a system made up of a large number of sensing, processing and actuating units mutually interacting, in such a way as to show the emergence of highly organised yet adaptive spatial-temporal dynamics. The smooth movements of a galloping horse are only the last, visible stage of an extremely complex phenomenon, where a pre-specified locomotion pattern, imposed at the highest level of the brain under motivational needs, is transferred to the lower levels of the neural assemblies of motor neurons, that implement the locomotion program. This represents an example of the so-called Central Pattern Generator (CPG), a neurobiological paradigm for locomotion generation and control, from molluscs to man [3], whose schematic representation is given in Fig. 1. In this architecture, sensory feedback is not essential for the execution of a single locomotion program, even if its use contributes to finely adapt actions to the environment. The CPG is therefore another example of complex system, and motion is its visible solution. With these considerations, our purpose was to face with the problem of locomotion generation and control through modelling the complex spatial temporal dynamics, shown by CPGs, in neuromorphic systems, joining them to a complex actuator structure, like a biorobot. The circuits taken into account to act as paradigms for this new kind of Robotics are also based on the theory of complex nonlinear dynamical systems: they are the so-called Cellular Nonlinear Networks (CNNs) [4].

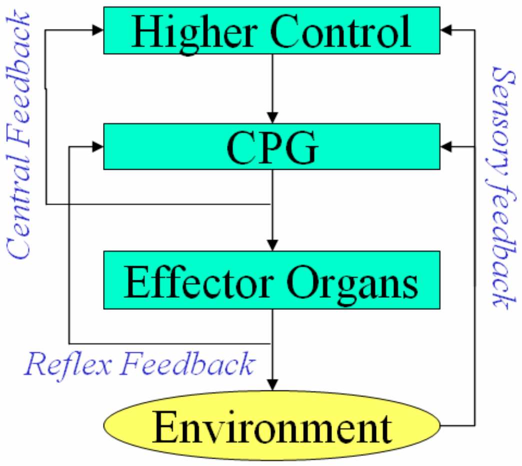
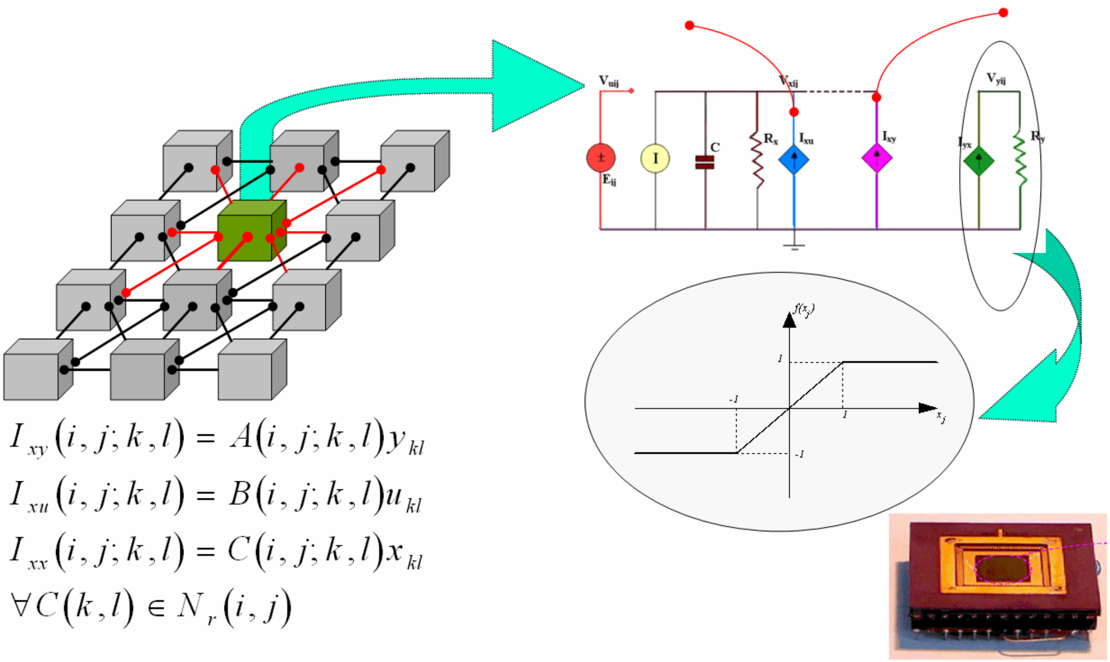


Fig.1 The Central Pattern Generator Scheme

The same architecture, able to generate locomotion patterns, was subsequently found able to generate also perceptual schemes for guiding motion activities towards the fulfillment of specific mission. In this paper these research lines are summarized, leaving details to the referenced manuscript.

Cellular Nonlinear Networks for locomotion

CNNs were introduced by Leon Chua in 1988, as large arrays of locally connected simple analog nonlinear cells, with the capability of being digitally programmable through the modulation of the local connections among the cells, under the form of *Cloning Templates* [5]. A schematic view of CNNs is reported in Fig. 2. In particular the state variable of each cell depends on the input, output and state values of the neighboring cells by means of the voltage controlled current sources outlined in the figure. Moreover, the output nonlinearity is very simple, a saturation function. In Fig. 2 the relations among the Cloning templates A, B, C, and the circuit parameters are also outlined. Finally, a VLSI implementation of the CNN architecture is presented. Nowadays technology allows to embed inside a single analog, digitally programmable chip, a number of 176 by 144 analog cells, able to realize a lot of functions in real time, assured by the analog implementation [6].



$$I_{xy}(i,j;k,l) = A(i,j;k,l)y_{kl}$$
$$I_{xu}(i,j;k,l) = B(i,j;k,l)u_{kl}$$
$$I_{xx}(i,j;k,l) = C(i,j;k,l)x_{kl}$$
$$\forall C(k,l) \in N_r(i,j)$$

Fig.2 The Cellular Nonlinear Network scheme and main characteristics

Fig. 3 Rexabot II

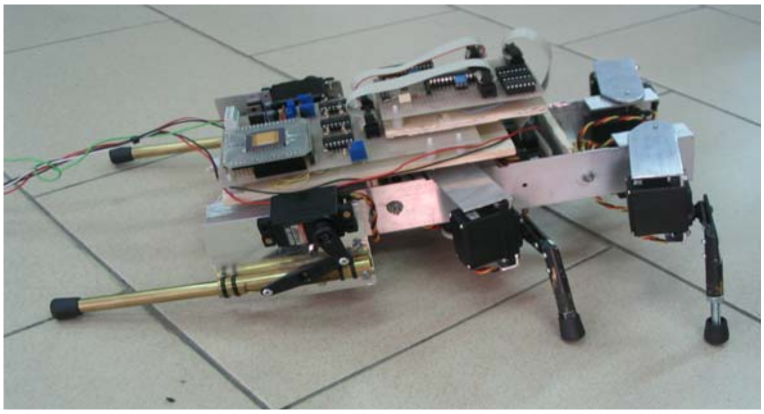


Fig. 4 Gregor I

Although being introduced at the main scope to act as real time image processors/computers, CNNs subsequently acquired the role of paradigms for the study of complex dynamics, including spatial temporal chaos and self-organization [4]. These lattices of simple non linear units have the property that the solution set shown by the network is much richer than that one shown by the dynamics within single units. As a consequence, new solutions “emerge”, which are often characterized by order and harmony. Moreover here computation is rather “wave based”, than “bit based” [7]. In this direction, these continuous time spatial temporal dynamical circuits and systems are the paradigmatic mirror of biological neural computation. CNNs, thanks to their programmability, allow to design and build space distributed networks of nonlinear systems (neurons) able to process in real time analog, space-distributed signal flows. Second order, spiking cells were designed and implemented by using continuous time nonlinear circuits, whereas diffusion-like synapses were chosen for the connections among the cells. The CNN designed belonged to the class of Reaction-Diffusion CNNs, able to generate particular traveling waves along the neurons of the CNN lattice: the so-called Autowave fronts [8]. These autonomous fronts were shown to possess the same qualitative characteristics as the signals in neural fibers. The design started from the dynamics of the single cell in the CNN array. This cell was designed so as to show, in the phase plane, a slow-fast, spiking limit cycle, typical of excitable media, like the neural one. The design was further tested against noise tolerance and was found robust enough to allow first a discrete component realization, and finally a VLSI implementation. Autowave fronts travelling through CNN neurons are extremely flexible: in fact their path along the cells can be efficiently controlled by using an input mask, i.e. a sensory input. The final aspect was to design a suitable functional transformation to realise a correspondence among the state variable of the CNN neural cells and the joint variables of the legs in the robot. This task was successfully achieved, realising multi joint biorobots where locomotion was the visible solution of the neural dynamics designed and realized at the level of the neural circuit of the controller (RD-CNN). Fig.3 shows REXABOT II, the first autonomous hexapod where all components are analog, to demonstrate that analog flows can do efficient computations to perform basic locomotion control patterns. The robot can control his locomotion patterns against the high degree of noise contained in the discrete component realization of the neural cells, hosted in the upper back part of the robot. The robot shows also a high graceful degradation level, since, cutting a cells out of the neural network, locomotion control can continue, even if slightly degraded, thanks to the re-synchronization of the neural array.

Once testing the robustness of this analog implementation of the CPG on arrays of RD-CNNs, an analog VLSI circuit was designed, realized and tested [9]. Fig.4 reports the first prototype of a cockroach inspired robot, controlled by the CNN based analog chip. The structure was re-designed to as to have higher dexterity in the front and mid legs, while leaving to the hind legs the role of generating a high forward thrust. The peculiarity of the CNN CPG chip is the possibility, thanks to a switched capacitor implementation, to modulate, through an external signal, the oscillation frequency of the neurons inside the chip. This can allow to drive very different families of actuators, from (slow) servomotors to (fast) piezo actuators. Fig. 5 depicts the implementation of this strategy on Rexaplif, an hexapod actuated by piezoelectric actuators driven by the same chip.

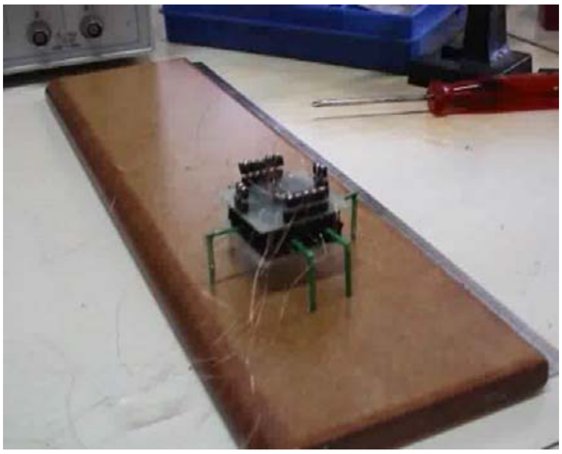


Fig.5 Rexaplif

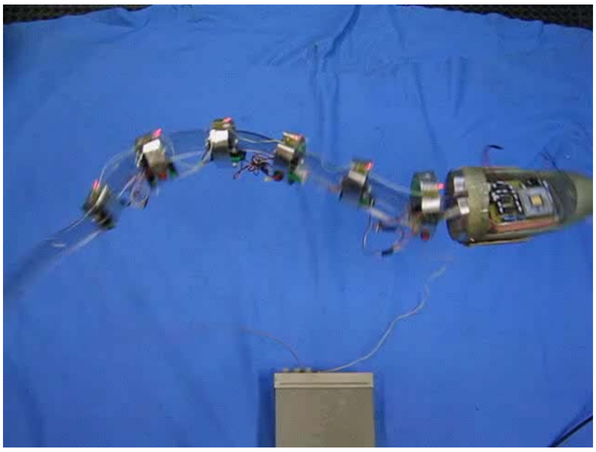


Fig.6 Lamprey robot

The generality of the approach allows to drive, with the same chip, completely different types of robot architectures. In fact, almost all animals are driven by the CPG paradigm. As an example, the same chip is once again used to control swimming in a Lamprey-inspired robot (Fig.6). The chip is clearly visible within the head of the robot. Actuation is, in this case, realized by servomotors, even if different kinds of actuators were tested, among which shape memory alloys, or McKibben muscles [10]. The implementation of the CPG paradigm through the RD-CNN paradigm allows to implement different locomotion patterns by changing the network topology and therefore the connections between the cells and the robot actuators. Another efficient approach consists in pre-designing a series of locomotion patterns by implementing a set of chemical-like synaptic connections among the neurons. In this latter case, the network topology remains the same, by a different set of template values is uploaded as a function of the particular locomotion pattern to be implemented into the robot. This last approach was called Multi-template approach, whose details are reported in [11].
Locomotion control of legged machines is a powerful technique, able to be simply and efficiently controlled. As an example, if we focus on the real time attitude control of a walking robot, with the aim to maintain a pre-specified roll and pitch reference in front of disturbance from the ground, this can be easily realized by a distributed layer of simple controllers acting concurrently with the CNN generating the locomotion patterns [12]. Fig. 7 and Fig 8 depict one of the results of the application of the analog control law on Rexabot III, a 18 Dof hexapod.

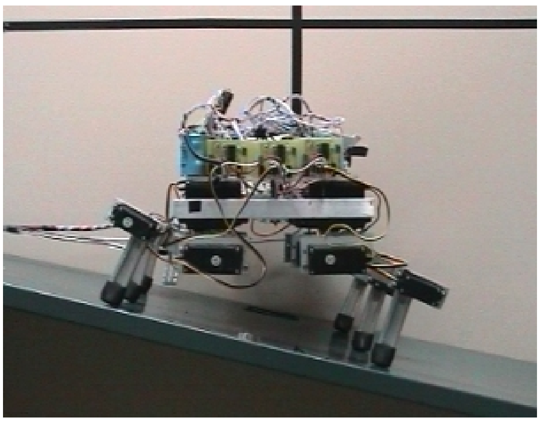


Fig.7 Rexabot III: attitude control

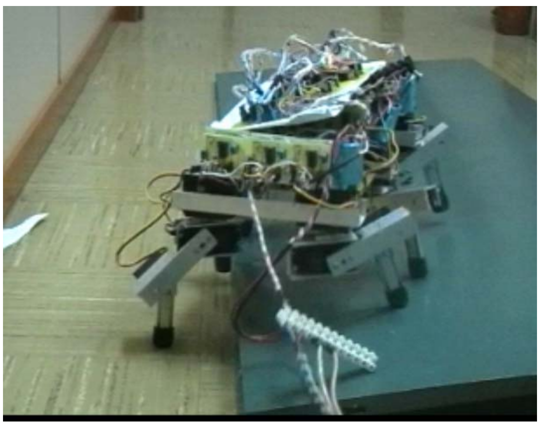
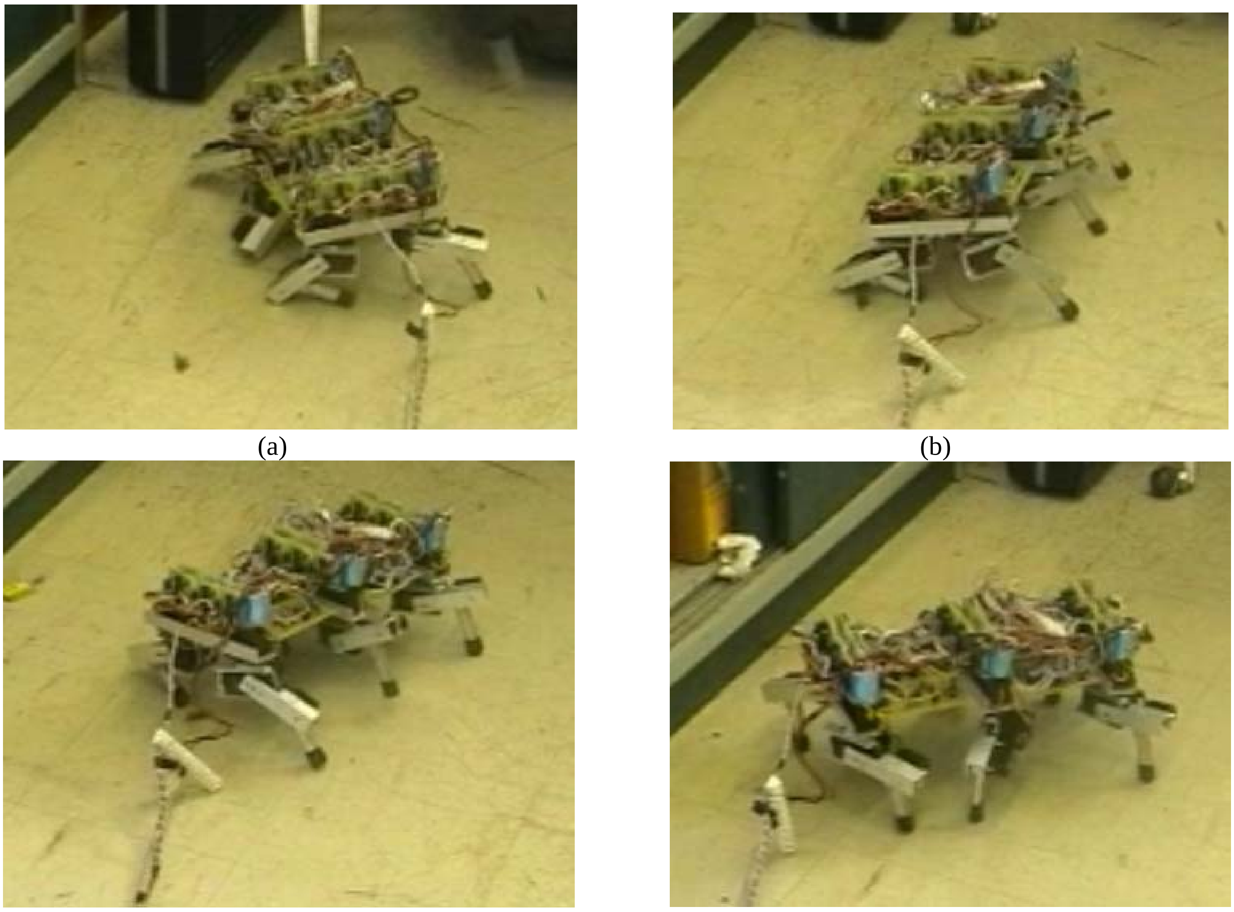


Fig.8 Rexabot III: walking and attitude control

The robot is able to maintain a given attitude, also while walking on very sloped grounds. Details on the design of the attitude control law and circuit are reported in [12]. Another important issue of this implementation is the distributed character of the control law. In fact, the reference signal, for any given single leg controller, is the roll and pitch signal for all the structure. As a consequence, the control action is active in front of any error, whatever leg is out of reference. The control law acts of the neural controller so that all the structure reacts in such a way as to reach a zero error condition. In such a distributed actuator network, this strategy greatly helps to escape from unforeseen situations. If for example, due to ground disturbance, one of Rexabot III legs is over loaded, and so attitude is no longer satisfied, the reference error propagation among the leg controllers guides the dynamics of all the CNN cells in order to solve the problem. This is a clear example of self organization and emergence of new solutions, typical of complex dynamics. What discussed is presented in Fig. 9, through a series of snapshots taken from a video.



(a) (b) (c) (d)

Fig.9: (a) Rexabot III front right leg is overloaded; (b)-(c)-(d) emergence of a recovery strategy coming from the integration among the CNN locomotion controller and the analog attitude controller.

Cellular Nonlinear Networks: from locomotion toward Perception

Drawing inspiration from perceptual mechanisms of biological systems, and relying once again on the RD-CNN paradigm, a bio-inspired framework for the sensing-perception-action cycle, was recently designed and implemented to be applied, as a first simple example, to the real time control of robot navigation, where the robot task is to move in an cluttered environment, trying to avoid randomly placed obstacles and to reach targets.

Such a framework can be divided into functional blocks (see Fig. 10). The starting point is a sensing block, which receives sensorial stimuli from the environment, dynamically clusters and uses them as initial conditions for a two-layer RD-CNN, which is the core of perception. The CNN parameters are chosen appropriately to generate the so-called Turing patterns [13], which are here exploited and used to form an internal state representation.

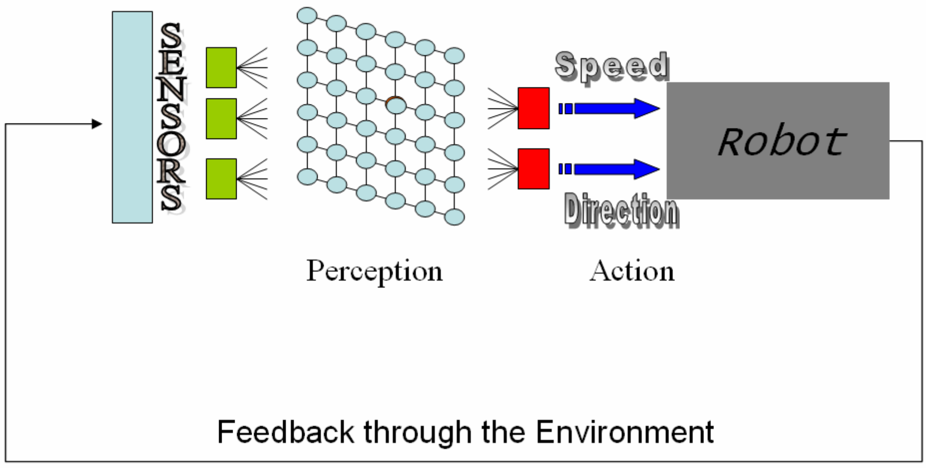


Fig.10: Scheme of the perceptual framework used for navigation control. The framework is divided into functional blocks, starting from the sensing layer to the robot motor control stage. The RD CNN extracts the needed information from sensors creating an internal representation through Turing Patterns generated. The learning process is guided by a motivation assigned to the robot.

The representation of perceptual states under the form of Turing Patterns in CNNs was a working hypothesis, inspired by works in Neurophysiology that report on the presence of non-spiking neurons in the cerebral ganglia of some mollusks whose high or low level plateau potentials maintain a specified pattern in front of desired behaviors [3].
Characteristics of the whole perceptual process are:

- ability to represent different environment situations as internal states;
- ability to associate a specific action to each internal state;
- ability to plastically modify these associations thanks to the experience.

Internal states (i.e. Turing Patterns) are the core of the perceptual process since they link sensing to action. They, on the one hand, are the result of the dynamic processing of incoming input stimuli and, on the other hand, represent different ways to interact with the environment. To meet these tasks, we use a CNN [13] as dynamical system and consider Turing patterns as internal states. In particular we use a two-layer four by four Reaction-Diffusion-CNN (with zero-flux boundary conditions) with appropriate parameters to generate Turing patterns [15].
Each pattern is associated with an action by means of a simple reinforcement learning. To perform its task, the robot is provided with no a priori knowledge and learns by means of trial and error, according to the experiments on Classical and Operant Conditioning.
The learning is implemented by two mechanisms: an unsupervised learning acts at the sensing block allowing the system to modulate the basins of attraction of the Turing patterns, while a simple reward-based reinforcement learning is devoted to build up the association between Turing patterns and actions. The latter is based on a simplified version of the traditional Motor Map algorithm see [14] and appendix therein.
The main differences of our work from that one reported in literature [16] is the introduction of dynamics in the system implementing the sensing-perception-action loop.
Dynamical systems have been successfully used in bio-inspired locomotion control of walking robots, as shown above. Nonlinear dynamical systems are used in place of a static neural network, for reasons of biological plausibility, versatility and much improved plasticity. This latter characteristics is obtained by imposing that the set of actions to be performed by the robot is not a

priori established, as in [16], but is the result of a simple, but effective learning mechanism, which improves the plasticity of the methodology.
The sensing-perception-action loop is modelled by using nonlinear dynamical systems like CNNs, exploiting their real-time implementation. The unsupervised learning algorithm has been introduced between the input sensors and the RD-CNN for the dynamical modulation of basins of attraction associated with Turing patterns. Moreover we have designed and used an oversimplified version of the MM, and added a contextual layer to support higher level navigation strategies.
In the case at hand, i.e. navigation in unstructured environment, the navigation task in a physical space is mirrored into a navigation, in the robot "brain", through a sequence of basins of attraction, each one corresponding to a particular behavior that has to be performed by the robot, in order to fulfill its mission.
Fig. 11 depicts a typical simulation result, while Fig, 12 reports an experimental phase, where the rover navigation is controlled by the mirrored motion through Turing patterns.

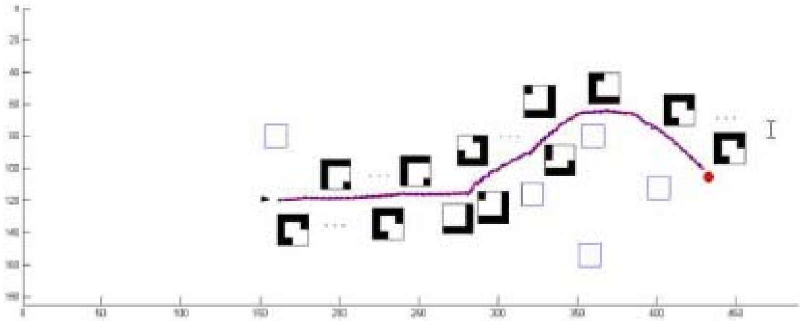


Fig. 11: Navigation through Turing patterns and associated actions in a simulated rover

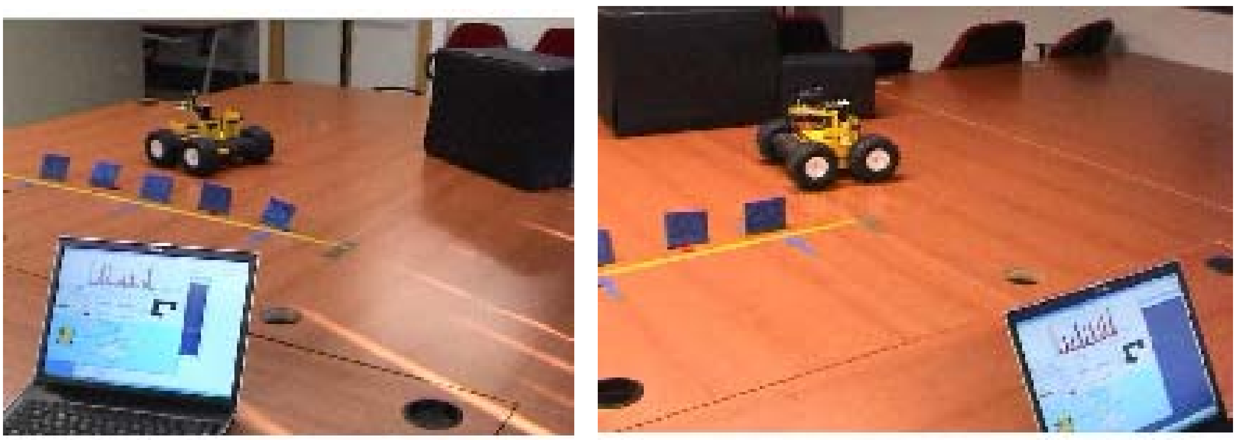


Fig.12: Two sequences of the robot navigation controlled by Turing Patterns, shown in the Laptop frame.

An interesting fact is that the cell structure generating wave fronts for locomotion control is structurally equal to that one generating Turing patterns. The two dynamics are obtained simply by a parameter modulation, in strict analogy with biological neurons, which attain different dynamics, although being structurally equivalent. The perceptual architecture was implemented in an FPGA based board architecture for the sake of simplicity and possibility to optimise the structure, but in the near future it is envisaged to have the structure within a whole analog circuit, devoted to generate both the perceptual states and the low level locomotion commands for the robot actuators. The actual robot prototype where the perceptual control is being implemented and that host the FPGA based hardware is Gregor III, depicted in Fig.13.

Fig.13: Gregor III: a cockroach inspired robot used as test-bed for the designed cognitive architecture within the SPARK project.

Gregor III is a new hexapod prototype, built to enhance the level of autonomy and dexterity with respect to the previous prototypes. It has a sprawled structure, very powerful hind legs (2 DoF each) used to provide a great push and support batteries and control boards; mid and front legs have 3 Dof each to enhance dexterity. The robot can implement both the CPG locomotion control and a decentralized motion control, inspired to the stick insect. To implement this new type of locomotion, Gregor III was endowed with touch and distance sensors, closed in loop with the network controlling each leg, which, in quite independent on the other ones, except for some local rules, to maintain the robot stability during walking.
This robust prototype, together with other legged and wheeled machines is currently being used within the EU funded project SPARK II, deriving to a former EU project SPARK, whose aim is to design and implement new insect-inspired architectures for action-oriented perception in bio robots [17-18].

Conclusions
In this manuscript a survey on a methodology for the biologically inspired control of locomotion in multi actuated machines in introduced. The strategy used CNN structures as basic paradigms for the emergence of locomotion patterns as steady state solution arising from the self organization of complex systems, like lattices of neurons, mainly locally connected, i.e. a CNN. The methodology, along the course of the last years, was assessed and subsequently implemented both in an analog, discrete component architecture, and in a VLSI chip. The chip was embedded into a number of moving, walking and swimming machines, showing its suitability to control in real time multi-actuated robots.
Subsequently, an approach to robot perception, inspired both by Neurophysiology and by Complex Dynamics was introduced. The formulated hypothesis considers the perception-action loop realized, at the high level of the brain, through a pattern forming process, within neuron lattices, where perceptual stated emerge as steady state membrane potential solutions as a function of the environment stimuli. The neuron lattice, once again formulated through the CNN paradigm, acts as a place where a progressive structuring of the environment information takes place at the aim to learn an abstract and concise representation of the environment, whose result is a pattern, i.e. a code within a CNN network. An action, associated through a simple reward function, is then applied to let the robot incrementally learn to solve a given task. In the mean time, a simple learning at the layer connecting the sensor signals to the CNN initial condition, act in such a way as to force all the set of environment information leading to the same action to belong to the same basin of attraction of the emerging pattern associated to that specific action.

The methodology, recently introduced, is currently being further assessed and enriched with information coming from Neurobiology about details of insect brain architecture and perceptual function, in order to arrive, in the near future to the introduction of an insect brain computational model applied to task solving in biorobots.

Acknowledgement

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The manuscript reports the activity on biologically inspired and perceptual robotics, performed at the University of Catania. Professors and students who worked in the various stages of the research are reported in the referred papers. They are explicitly acknowledged.

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