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Engineering central pattern generated behaviors for the deployment of robotic systems

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ABSTRACT

In order to face with various contexts and situations, autonomous robots should be endowed with many different sensors and behaviors. These requirements pose new challenges such as the coordination of multiple parallel activities and the efficient use of the limited sensorial and cognitive resources. These challenges are often tackled by relying on a priori and well defined coordination schema among behaviors, and on fixed periodic or ad hoc monitoring strategies. Our working hypothesis is that adaptive control strategies, inspired by natural cyclic processes, can be used to cope with these problems. However, the development of these flexible strategies may result hard to be modeled and implemented. Recently, the possibility of abstracting an implementation view into an architectural design is getting more achievable. Hence, in this paper, we propose a modeling framework that allows developers to model simple behavior-based robotic systems enhanced by the use of Central Pattern Generators (CPGs) for modulating the sensor-motor loops. Different from other approaches, the use of CPGs, here, is to efficiently exploit the limited sensorial and cognitive resources, and to coordinate the multiple activities the robot is endowed with, by balancing sensors elaboration and action execution. The framework can use these models to generate robotic control executable code for analysis purposes. In this paper, we focus on parallel behaviors managing analysis.

1. Introduction

Due to the variety and complexity of real environments, autonomous robots should be endowed with many different capabilities/behaviors in order to face with various contexts and situations. This issue imposes the need of control systems to assure an efficient use of the limited sensorial and cognitive resources, and to coordinate the multiple activities the robot is endowed with, by balancing sensors elaboration and action execution. Most of robotic control systems, in order to cope with these issues, typically rely on a priori and well defined coordination schemas among behaviors (in order to manage behaviors interaction) and on fixed periodic activation of functions that elaborate perceptual inputs (in order to reduce the computational burden), or ad hoc policies for modifying the sensor elaboration strategies in a more efficient way. Our working hypothesis is that adaptive control strategies, inspired by natural cyclic processes, can be used to cope with these problems.

Many bio-inspired works, adopting Central Pattern Generator (CPG) mechanisms for regulating the robotic control systems, have been presented in the literature [1–5]. In particular, within the robotic field the CPG concept is adopted by the researchers for generating efficient control strategies, especially for legged robots, drawing inspiration from biological locomotion principles [6–8]. In general, the CPGs are modeled as central neural units able to generate rhythmic patterns without the need of any sensory signal from the external environment to produce them. The term *central* indicates, in fact, that the sensory feedback is not needed for generating the rhythms. However, these rhythmic patterns can be altered or modulated due to some internal or external needs, events or goals (e.g., changes in heartbeat rhythms due to a state of anxiety or locomotion speed variations caused by unexpected events). Hence, while a sensory feedback is not requested in order to generate a rhythmic motion pattern, its role is crucial in shaping and modulating the final motion pattern [9].

It has been proven that these rhythmic generator mechanisms are involved in many rhythmic activities of living beings [10] at different time scales. The oscillatory processes provided by CPGs play a fundamental role not only both in perceptual (for example, in visual processing and olfaction [11]) and motor systems (for example, in the generation of rhythmic movements such as walking and breathing [12,13]), but also in cognitive activities

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(e.g., memory formation [14]) [15]. Typically, the CPG models presented in the robotics literature mainly refer to the capability of controlling and regulating rhythmic movements, in particular for locomotion [16,17]. Up to our knowledge, the approach of [18] is the only one that deals with the regulation of the sensory input over and above the motor output. In particular, in [18] the authors proposed a particular mechanism, named Adaptive Innate Releasing Mechanism (AIRM), applied to Behavior Based Robotic (BBR) architectures, able to both rhythmically activate the robot behaviors based on internal innate releasing mechanisms and adapt the frequencies of the associated sensory readings depending on the robot goals and on the external environment changes. Namely, the authors proposed a control system for sampling the perceptual input that, similar to a CPG, achieves a quasi-periodic activity (i.e., possesses at least an active and an inactive phase) and is flexible (i.e., dynamically adapts its period with respect to external and internal requirements).

In [19] AIRM mechanisms were modeled as networks of neurons (AIRM-nets) capable of autonomously generating oscillatory patterns, while in [20] a Differential Evolution (DE) genetic algorithm was used to dynamically estimate suitable AIRM-nets threshold configurations.

Previous works only presented the proposed approach in specific case studies. Here, we assess the general framework for the development of AIRM-net based robotic controllers from a software engineering point of view. We will present an *how to use* example by showing the steps for constructing a CPG-based robotic architecture by means of our AIRM-net framework. Some results will be shown concerning a robotic application where both attractive and repulsive parallel behaviors are considered.

2. Material and methods

Typically a CPG is modeled as a biologically inspired rhythmic system consisting in neural oscillators, regulating living beings' activities. Here, we re-engineer the AIRM-net model proposed by [19] for regulating the activations of the behaviors composing a BBR control system. In this system the robotic sensory feedback is deployed to modulate rhythmic patterns that control the activation of robot behaviors, and to synchronize such behaviors [21,2]. Our aim is to provide a general framework for the development of CPG-based robotics applications. In the following sections, we will briefly introduce the AIRM-net design and the genetic algorithm used to properly set the network parameters.

2.1. AIRM-net controllers for robotic behaviors

In [18], the authors proposed a model of attentive behavior represented by a Perceptive Schema (PS), a Motor Schema (MS) and a triggering mechanism that acts as a CPG. The main role of a CPG within the behavior schema is to rhythmically modulate the activation of the PS of the behavior and, consequently, its MS, by producing a periodic and adaptive sampling of data coming from sensors (see Fig. 1). Such triggering mechanism, called AIRM (Adaptive Innate Releasing Mechanism), can be dynamically adapted to circumstances and so has an adaptive frequency depending on the sensor input changing rate. Moreover, it has been shown that this mechanism drastically reduces the computational load associated to the sensors elaboration [22]. The proposed adaptation model relies on the assumption that such internal rhythm generators that principally manage, in this case, perception and action activities, play a fundamental role in generating expectations on events occurrence in time and that the temporal trend of the external stimuli drives, in some way, the internal rhythms [23,24]. For example, in [25], the authors used oscillators with the aim of adapting their period to the dynamics of the events occurring in time by generating an external rhythm that was able to entrain the internal one. The entrainment process of neural rhythms was connected to the perception of the time and to the ability of tracking events in time [23,24].

In [19], the authors designed a neural net (AIRM-net) to implement the AIRM controller, able to generate triggers to the PS and the MS. The [19] CPG model does not aim at representing a mimic of the biological counterparts, but it provides a functional imitation, implemented by using neural networks, in order to obtain robotic control systems with better performance (as shown in [22]). The proposed net was divided into four subnets named INET, INCR, DECR and ZEIT connected according to the schema in Fig. 2. In the following, we just recall some useful details of the AIRM-net (for a full description refer to [18]).

The ZEIT module is responsible to produce the releasing trigger (ρ) to the behavior (b) PS/MS at a time interval, named clock period or p_b, used to space out two successive triggers. p_b is initially set to its maximum value (p_{bmax}). Without the modulation of perception this value is kept constant and the ZEIT module triggers the INET module every p_b instants of time. In Fig. 3a, a general ZEIT module with $p_{bmax} = 2^n$ is shown. This sub-network is represented by three layers: the first generating the baseline rhythm, the second is responsible for the modulation of the period, while the third is for the generation of the trigger signal ρ.

The ZEIT module produces the frequency as a function of the changing rate of the sensory input σ of the behavior, evaluated by the INET module. Indeed, INET value activates the DECR or INCR module depending on the trend of σ. For example, the INCR block compares the value of the incremental ratio of σ to the thresholds of n specific neurons (CL_i in Fig. 3b) and if it is greater than the corresponding neuron threshold, this sends an impulse to the ZEIT module modifying, in this way, the period p_b. The DECR module (see Fig. 3c) estimates the incremental ratio value in order to inhibit neurons in the INCR module and, consequently, decrements the value of p_b. Hence, the ZEIT module interacts with the INCR and DECR modules in order to change the clock period according to the increasing or decreasing input variations of INET. The

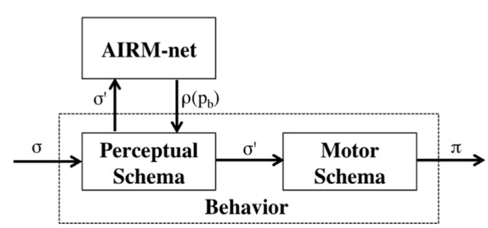

Fig. 1. Schema theory representation of a robotic behavior model, endowed with an AIRM-net controller, regulating the sampling rate of sensory readings and motor actions.

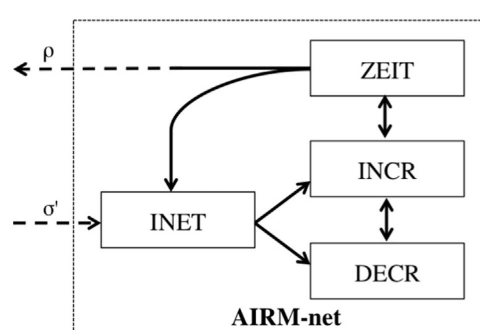

Fig. 2. AIRM-net controller block diagram.