INTERNAL REPRESENTATION OF THE ENVIRONMENT IN COGNITIVE ROBOTICS

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Abstract

Novel theories have recently been proposed to try to explain higher cognitive functions as internal representations of action and perception of an embodied autonomous agent in a situated environment. Using neural evolutionary robotics, a new concept of collaborative control architecture allows construction of a behaviour-based system as a result of interactions between the control system and both the external and internal environments. The full separation achieved between the inner world of the autonomous agent and the real external world gives some insight into how comprehensive understanding on robot sensing and learning can be obtained. Two experiments, the first on generation of walking gaits for the Aibo robot and the second on a two-sensor, two-motor simulated robot orbiting around an object illustrate the performance of the proposed paradigm and lead to discussion of concepts in the robot's inner world, emerged from the interaction with the environment when completing a task.

Key words: Context understanding; Collaborative intelligent architecture; Cognitive robotics; Robot learning; Ambient robotics

1 Introduction

The study of cognitive systems for engineering purposes involves the creation of artificial systems that reliably exhibit some desired level of cognitive performance or behaviour [1]. In the age of computers as boxes, traditional approaches to modelling cognitive systems were computational [2,3], based on (i) utilizing the standard tools and concepts of the theory of computation, and (ii) understanding human cognition as to study the mind/brain in abstraction from its real-world environment. Later, theories were proposed that tried to explain higher cognitive functions as *internal simulations* of action and perception [4] of an embodied autonomous agent (a robot) in a situated environment (at home, for instance), leading to a different vision from the former contrasting frameworks [5]. Brooks' engineering approach to the construction of computerized agents extends the initial Fodor's methodological cognitivism by considering intelligence as situatedness [6], however the world of computerized agents was still a world of computers with layered structure situated in environments. Gibson's ecological approach [7] offered a theory for cognition as an ecological (natural) science in contrast to the precedent view of computational science, a science of the artificial [8]. In this sense, dynamicist theories has been recently proposed as alternative for handling cognition [9], considering cognitive agents as dynamical systems that can be understood dynamically. Hence, much of the current work in embodied cognitive science is in a sense returning to its cybernetic roots [10], focusing on agent–environment interaction and bodily and sensorimotor mechanisms [11,12]. Machine learning approaches including *artificial neural networks* [13], *behaviour-based* systems [14], *artificial life* [15] and *evolutionary computing* [16] fit this new paradigm based on *dynamical coupling* [17]. The architecture concept presented here can be classified within these latter theories, using neural evolutionary robotics in a novel modular form for construction of a behaviour-based system.

Modularization is accepted for all the approaches cited as the most naturally occurring structure able to exhibit complex behaviours from a network of individually simple components, which interact with each other in relatively simple ways. Collaborative elements are usually information-processing *software* units, such as neurons, or dynamically *simulated* entities, such as bees with swarm intelligence, or flocks of birds, schools of fish, etc., so that the coordinated behaviour of the group *emerges* from the interaction of these simple agent behaviours. The approach proposed is also based on simple collaborative information-processing components, albeit as close as possible to the *hardware* devices (sensors and actuators), called *intelligent hardware units* (IHUs), embodying a physical autonomous agent to design a new ambient architecture concept. Constructivist robot control architectures are usually decomposed into a number of layers, each with access to sensors and motors, and each responsible for generating different levels of behaviour, such as ‘collision avoidance’ or ‘map-making’, the so-called *subsumption architecture*. However, retaining some of the ideas of von Foerster’s work [18], reproduced by Ziemke [10], by separating these functions from the totality of cognitive processes, the original problem is abandoned and transformed to a search for mechanisms that implement entirely different functions.

We demonstrate in this article that a modular architecture based on IHUs allows the emergence of behaviours as a result of the interactions of a collaborative control system with both the external and internal environments, in that it implements the von Foerster concept of *double closure*: an embodied agent can be *autonomous* and *organizationally closed*, but at the same time *structurally coupled* to the environment it is situated in. Hence, the architecture obtained is not based on internal models trying to exactly model the environment, but the internal model that emerges constructs a reality based on interaction with the environment that is useful for reaching the proposed goals. In this form, our approach is interesting from three points of view: (i) Behaviour-based robotics: a novel modular concept based on hardware elements for the behaviour of autonomous agents is defined; (ii) Control engineering: a fully collaborative control architecture based on IHUs with internal representation of perception is developed; and (iii) Ambient robotics: a possible approach to the human-robot interaction problem is postulated using internal robotics.

In the next section, the modular concept is introduced for autonomous agent control, with IHUs proposed as possible modules for a modular implementation of autonomous agents control system. Section 3 discusses the new paradigm and shows, using a control engineering discourse, how this approach allows the generation of a truly inner world with internal representations of perception. The full separation achieved between the inner world of the autonomous agent and its external real world provides some insight into how the human–robot interaction can be improved from a robot cognitive point of view, dealing human as a part of the environment. A simple experiment on a two-input, two-output simulated robot and experiments for the generation of walking gaits on the Aibo robot, a complex task in a complex environment, illustrate the performance of the proposed paradigm when completing a task. Finally, some conclusions and proposals for further research conclude the article.

2 Intelligent Architecture: A Tactical Modular Concept

For the control of an artificial autonomous physical agent, sensory information from the environment must be obtained through sensors. This information must then be processed and used to guide the actions of the agent so that it can perform the task in question. When the number of sensors is large and the task at hand is complex, usually implying interaction with objects and people, difficulties arise on how to integrate all the sensory information in order to guide the action [5]. We propose modularization to solve this problem. In the design of modular neural controllers, most works have been influenced by the mixture of experts of Jacobs et al. [19]. Their basic idea was to design a system composed of several networks, each of which handles a subset of the complete set of cases required to solve the problem. Their system has been widely used and improved upon by several authors in different classification problems [20,21]. In the case of evolutionary robotics, Tani and Nolfi [22] improved the Jacobs architecture for robot control. Recently, Paine and Tani [23] studied how a hierarchy of neural modules could be generated automatically. Lara et al. [24] separately evolved two controllers that performed different tasks, then the connections between the controllers were evolved in an additional step to generate a single controller capable of performing both tasks. Despite all these good results in modular robot control, none of the studies focused on sensor fusion, and only robots with a small number of sensors and actuators were used. Furthermore, all the studies cited divided the global task into a set of easier sub-tasks, so that when combined, the robot performed the global task required. Each module was implemented by a monolithic neural controller taking the sensor values as inputs and the commands for the actuators as outputs. Even though all the studies were successful, it has been not reported how this type of neural controller could control more complex robots with a greater number of sensors and actuators [25].

We propose tactical modularity approach as a paradigm that should generate modularity at the level of the robot devices (sensors and actuators) that implement a required sub-task. This means that, once a sub-task has been determined for the robot, the tactical modularity concept is applied to implement the sub-task using the sensors and actuators at hand. Modularity is implemented by designing a decentralized controller composed of small processing modules around each of the robot devices, called IHUs. A schematic diagram of an IHU is shown in Fig. 1. Every IHU comprises a sensor S_i or an actuator A_j and an artificial neural network (ANN) that processes the information arising from the associated device: it receives sensor information, $y_i = ANN_{S_i}(\cdot)$ or it sends commands to the actuator, $u_j = ANN_{A_j}(\cdot)$. All the IHUs are interconnected to each other to be aware of what the other IHUs are doing,

$$\begin{aligned} y_i &= ANN_{S_i}\left(s_i, \mathbf{y}_{(\backslash i)}, \mathbf{u}\right) \\ u_j &= ANN_{A_j}\left(\mathbf{y}, \mathbf{u}\right) \end{aligned} \tag{1}$$

with $s_i = S_i\left(out_i\right)$, $\mathbf{y} = \{y_k\}_{k=1}^{p}$, $\mathbf{y}_{(\backslash i)} = \{y_k\}_{k=1}^{p \backslash i}$, $\mathbf{u} = \{u_k\}_{k=1}^{m}$, $in_j = A_j\left(u_j\right)$. Each particular neural processor translates information received from the sensor S_i (or from the network) to the network (or to the actuator A_j). A neural controller for a simple robotic system with two sensors and two actuators is depicted in Fig. 2. Only nodes into the neural networks directly associated with physical devices manage real world signals; all the other nodes deal with internal representations of the world.

Putting computational power at each sensor is not a new idea [5]. The novel ap-

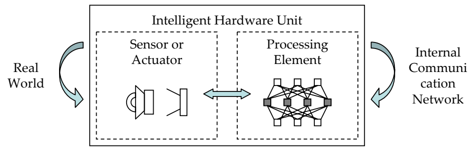

Fig. 1. Schematic diagram of an Intelligent Hardware Unit.

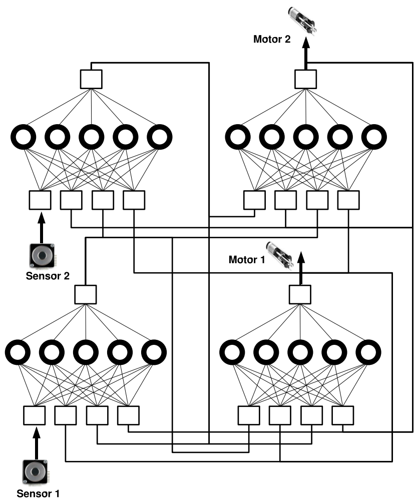

Fig. 2. Application of four IHUs for control of a simple robot composed of two sensors and two motors.

proach presented here is the simultaneous introduction of computational power into each actuator that generates internal representations $(\mathbf{u}, \mathbf{y})$ of the external world $(\mathbf{in}, \mathbf{out})$, and the design of a complete information-sharing network between all devices. The approach involves building simple but complete systems, rather than dealing with the complexity problem by dividing cognition in sub-domains. Using a neuro-evolutionary algorithm, neural nets learn how to collaborate with each other and how to control associated elements, allowing the whole robot to perform the required sub-task. The co-evolutionary algorithm uses genetic procedures to teach networks how to cooperate to achieve a common goal, i.e., the sub-task to be implemented, with every network having its own and different vision of the whole system. The Enforced Sub-Populations (ESP) algorithm [26,27] was selected during experimentation to evolve the network because of its good performance in co-evolutionary processes.

3 Internal Representation of the Environment

In this section, the proposed IHU-based tactical modular architecture is justified as a dynamical approach to ambient cognitive robotics using a control engineering perspective. Our aim is to demonstrate that the proposed network structure of IHUs provides the autonomous agent with an 'inner world' based on internal representations of perception through the completed task rather than an explicit representational model, following the ideas of internal robotics of Parisi and the double closure scheme of von Foerster. Hence, we are interested in building a simple but complete system rather than in dealing with the complexity problem by dividing cognition into sub-domains.

3.1 Control engineering perspective

Feedback is a simple control structure that considers the relationship between outputs and inputs in a plant (sensorimotor control) [28]. A typical single-input, single-output (SISO) feedback control system is depicted in Fig. 3, for which the *inner world* is defined as the part of the control system corresponding to controller-based units, $s =$ Sensor(out), $y =$ Conditioner(s), $u =$ Controller(SP_{Int}, y), and $in =$ Actuator(u). Similarly, the *outer world* is defined as the part of the control system corresponding to process-based units, i.e., the physical world in which the autonomous agent is situated, $out =$ Process(in). From a basic control engineering perspective, so that the whole system reaches the set point (SP), the control elements (inner world) must be designed using a model as close as possible to the

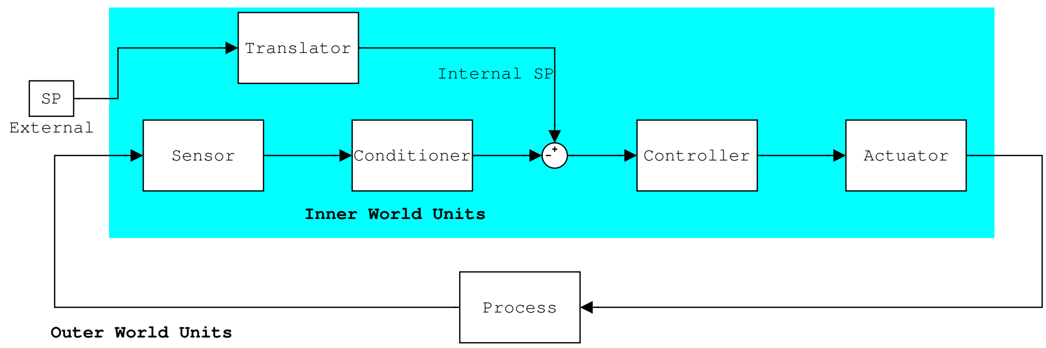

Fig. 3. A typical SISO feedback control system.

outer world, the so-called *process model*. Controller design procedures in control engineering are traditionally model-based, so the performance of the whole system depends on how well the process has been modelled: the internal model of the outer world used to generate the inner world must be as close as possible to the outer world. However, how closely human behaviour can be modelled?

A particular element that can help in understanding the concept is the role of the SP. For effective comparison of blocks in Fig. 3, the external SP must be translated to an internal SP based on the same units for the controller as for the inner world. For example, a thermostat translates external SPs from temperature units to voltage units in a range similar to that for the conditioner. It is usually assumed that this conditioning is known to the control engineer designing the control system, so sensors and actuators are considered as part of the process, leading to clearer control design: a correspondence can be established between outer world (in, out) and (s, u). However, when this knowledge is not available, sensors and actuators are not predetermined, or they are affected by the environment in an unpredictable manner, then the relationship between the conditioner, controller and translator is no longer a simple additive process. Unlike in traditional approaches, a learning procedure or teaching module must exist for designing or modifying the agent's internal representations and intentionality. The internal translation of the external SP, which is selected in a certain sense, should affect both control elements (conditioner and controller) in an unknown, possibly non-linear manner.

These elements comprising the cognitive architecture of the autonomous agent are responsible for adapting the relationship between the autonomous agent (embodiment) and the environment (situation):

- The **conditioner** is a control element that adapts what the sensor captures from the outer world to what the robot architecture perceives in its inner world, considering the internal SP (the task at hand).
- The **translator** is a control element that translates the external SP, which is in fact a goal associated with a task, as an interpretation of the outer world. It is a learning function for the whole inner world system.
- The **controller** is a control element that relates internal perception of the outer world in the form of inner world units to accomplishment of the task at hand, interpreted as an internal SP in inner world units. It drives the actuator to change the body–environment situation (the robot-human relation). It needs continuous but not exhaustive learning to continually adapt the body to the environment.

Broadly speaking, the behavioural architecture depends on the goal (goal-directed training) interpreted by the translator, on the environment (outer world) interpreted by the conditioner, and on the body (control, sensor and actuator) acting through the controller. Information from the environment is *mentally presented*, instead of *mentally represented*: there is no need, as in the traditional approach, to consider any accurate correspondence between the internal model and the real world via a process model. The internal model is built from interaction of the body with the environment; however, in contrast to Parisi [4], it does not try to exactly imitate the world, but is an interpretation of it [29]. The important point is that the agent's view of the outer world makes sense to the agent himself. Experience and information obtained from the interaction with the world are therefore highly subjective.

3.2 The internal model

Sensor processes (hardware–software perception, $out \mapsto s \mapsto y$) and motor processes (software–hardware motion, $y \mapsto u \mapsto in$) are separated. However, feedback from the outer world is not enough to achieve the von Foerster concept of *double closure*:

> "The meanings of the signals of the sensorium are determined by the motorium; and the meanings of the signals of the motorium are determined by the sensorium."

Therefore, perception and motion must be connected to each other in such a form that information has its origin in this creative circle. Motor stimuli must also be sent to the sensor elements to 'predict' what to sense upon real sensation in the outer world: $out \mapsto (s, u) \mapsto y$. In terms of control engineering, an internal model control (IMC) structure [30] can be chosen to introduce the concept that an information flow exists from the actuator control signals to the conditioner (Fig. 4). These signals model the environment, and hence a *modeller* is defined for both, modelling the environment and conditioning the outer world to the inner world units (Fig. 5). The inner signals sent by the controller are fed back to the modeller, instead of real world signals from the actuator, since this structure does not pretend to exactly model the world, or to obtain a subjective internal representation of the outer world. Extension of the proposed SISO control to a typical distributed multi-input, multi-output (MIMO) system (Fig. 5) results in a control system exactly the same as our proposed network of IHUs (Eq. 1), as shown with the two-input, two-output

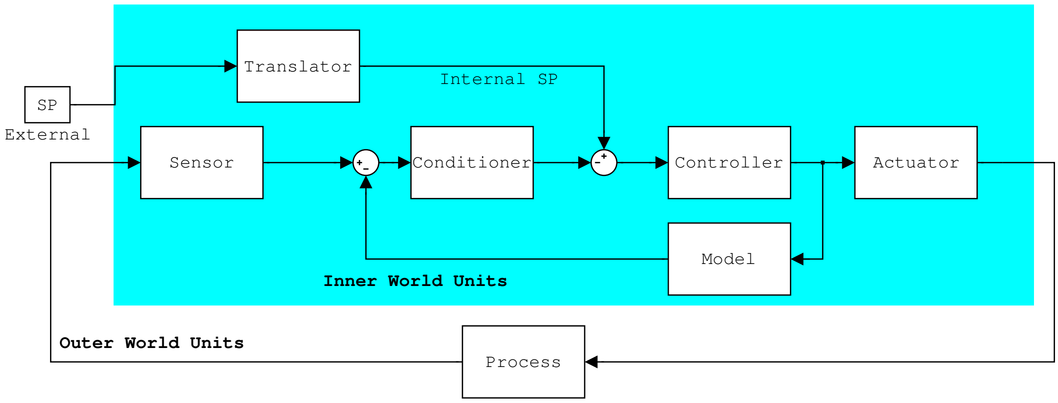

Fig. 4. Feedback control loop with internal model control.

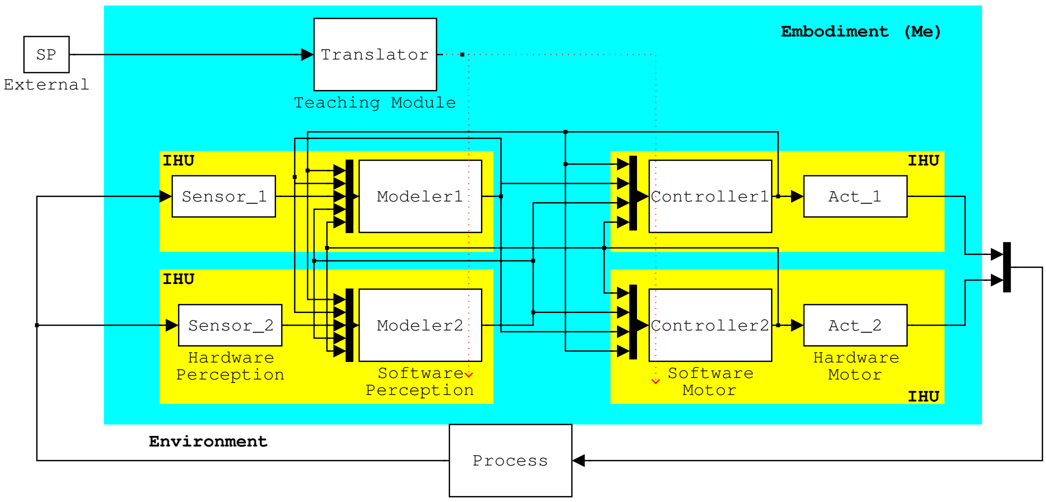

Fig. 5. Behavioural robot architecture designed on collaborative IHUs in the form of a MIMO and decentralized control architecture.

IHU-based network in Fig. 2.

4 Experiments and Discussion

Two experiments have been designed to explain the contributions of the proposed methodology: the first generates a walking gait for a quadruped as a complex task to validate the proposed architecture; and the second is a two-wheeled simulated robot completing a simple task to illustrate and discuss the internal world generated for the proposed paradigm.

4.1 Validating the collaborative intelligent architecture

To evaluate the proposed architecture as a valid control architecture completing complex tasks, we selected generation of a walking gait for a quadruped in a highly complex robot with several degrees of freedom (DOFs). A total of 31 sensors and actuators are managed by the tactically modularized architecture. Two main approaches exist for designing walking robot controllers: (i) using a walking algorithm manually designed by an engineer that indicates at any step the position of every joint of the robot [31], so the resulting gait is perfectly engineered one; or (ii) using dynamic coupled CPG (central pattern generator) equations for non-linear oscillators built on neural networks. We implemented the latter approach [32].

Firstly, our architecture was directly applied to the robot to evolve controllers for generation of a walking pattern. Following the CPG approach, the architecture was implemented using continuous-time recurrent neural networks (CTRNN) [33] and a fitness function was developed obligating the robot to acquire a determined gait style, based on the Sony walking style. Unfortunately, none of the controllers evolved for different fitness function variations for the walking task were able to take steps; the high dimensionality of the search space being identified as a potential problem, sequential evolution was then considered. Architectures implementing sequential evolution based on CPGs for evolving walking gaits [32] have never been applied to a robot as complex as Aibo, with so many DOFs. Our sequential planning first evolved isolated CPG oscillators, so the system generated a mean value for the range of movement of each joint, with maximal variance. In a second stage, CPGs were replicated in all the legs. Required synchronization between CPGs for implementation of a simple walking gait implies a phase relation of π radians between pairs of joints of all types. The fitness function yielded continuous oscillatory movement with this phase relation. During experiments, after 14 generations, 90% of the evolved networks were able to generate counter-phase oscillatory patterns. The final stage is coupling between layers of joints. From the previous stage, three different oscillating layers were obtained with four joints of the same type oscillating together in a walking phase relationship. Interconnection of the three layers is then required to complete the architecture as a whole to obtain coordination, allowing the robot to walk. Walking behaviour was obtained for more than 85% of the populations [1] .

4.2 Discussion for a generated internal world

Generation of a walking gait resulted a valid experiment to evaluate the proposed architecture as a valid control paradigm for solving complex tasks on general complex robots. However, main contribution of the proposed method is not limited to deal with increasing complexity, but the generation of internal world as long as the task is being accomplished. In order to illustrate it, complexity has been reduced for an easier discussion: the goal in this second experiment is to obtain an autonomous robot able to find a square object in the middle of the simulated environment, starting from a randomly selected point and then orbiting around the object in an endless loop at a close distance. This behaviour emerges from the cooperation of four IHUs associated with two infrared sensors placed at the upper-left corner of the

[1] Visit www.ouroboros.org/evo_gaits.html for walking sequences for the simulated Aibo and the real robot.

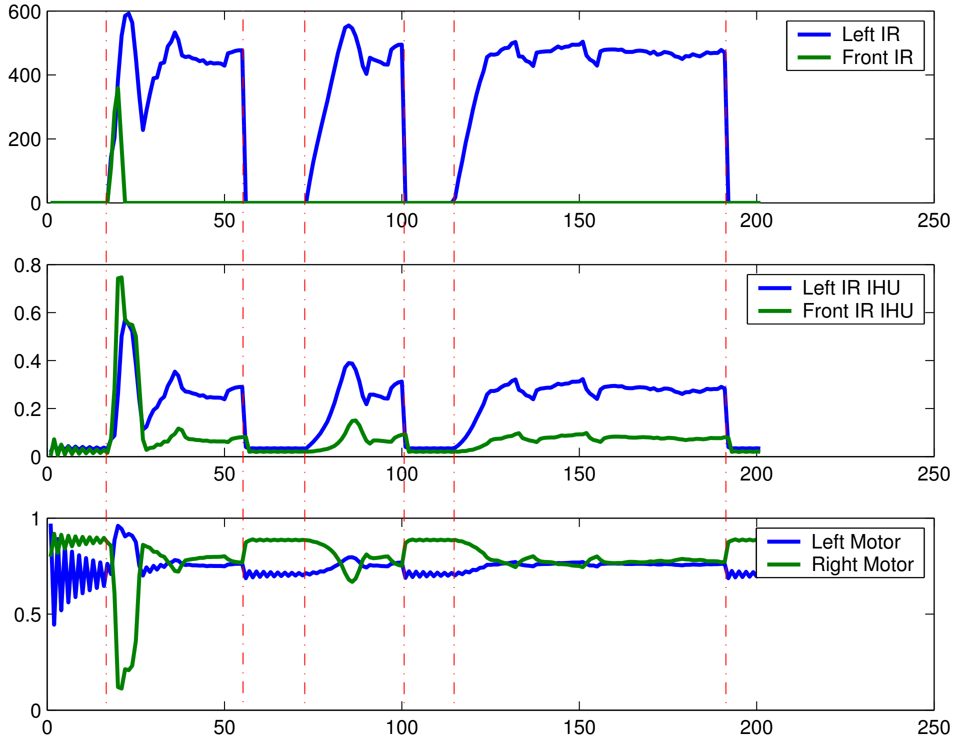

Fig. 6. Signals from sensors, IHU sensor translation and IHU motor actuation after learning for the orbiting simulated robot experiment.

robot, one pointing to the front (Front IR) and another pointing to the left (Left IR), and two motors driving two wheels placed at the bottom of a square platform. A third free wheel at the front gives stability to the whole robot, but offers no control. Sensors were modelled that can detect objects within a limited range, similarly to real IR sensors, such that they are not detected when they are not close enough. The physics of the robot movement was emulated using the Webots simulator [34]. This emulation included a small bias on motor values due to imperfections, and noisy effects were taken into account. Each IHU is implemented by a static feed-forward ANN with a sigmoidal activation function.

Signals obtained from a complete experiment involving 200 steps taken by a trained robot are depicted in Fig. 6. The top plot shows actual IR sensor readings, the middle plot shows IHU sensor translation for the signals, and the bottom plot shows the IHU actuator control commands sent to the motors. It is evident that the IHU sensors have learnt to translate sensor readings in a nearly exact scaled form, except for the instant at which the robot finds the object. In such a situation, both IR signals are magnified, but they are proportionally inverted; so the internal model is a distortionated version of the reality, but it manages for accomplishing the task. The experiment starts with null signals being sent from the IR sensors to the associated IHUs because no object is detected. These signals are translated to noisy signals for the IHU sensors because signals received from the IHU actuators are noisy. However, the robot has learnt to send a higher driving control to the right motor than to the left one, obligating the robot to turn around. At a certain moment, the robot finds the object and turns until it can orbit around the object. Owing to the sharpness of the central object to be detected and orbited, and the use of static feed-forward networks, the robot loses contact with the object when orbiting. During this time, the robot has learnt that, as previously, it is better to always turn to the left by increasing power on the right motor and decreasing it on the left motor, in order to reach the goal.

5 Conclusions

A new paradigm is presented based on modularity that explains higher cognitive functions as internal representations of action and perception of an embodied autonomous agent in a situated environment. In tactical modularity, subdivision into modules is performed at the level of the physical elements of the autonomous agent (sensors and actuators) involved in accomplishment of a task, the so-called *intelligent hardware units* (IHUs). The IHU-based tactical modular architecture proposed has been justified as a dynamical approach to cognitive robotics using a control engineering perspective. It has been demonstrated that a network structure of IHUs provides an autonomous agent with an 'inner world' based on internal simulations of perception rather than an explicit representational model. Thus, the full separation achieved between the inner world of the autonomous agent and its external real world gives an insight into how the human-robot relation can be resolved. The architecture proposed was validated for generation of the walking gait of a quadruped in a highly complex robot with several DOFs. A total of 31 sensors and actuators are efficiently managed by the tactically modularized architecture to accomplish the task.

The tactical modular architecture is focused on the emergence of behaviour and not on deliberative interpretation of the process; however, it can facilitate the integration of both reactive and deliberative controls. Further studies should be developed to analyse in detail the functionality of the translator module and its ability to integrate both types of control.

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