Procedia Computer Science

Volume 88, 2016, Pages 102–106

7th Annual International Conference on Biologically Inspired Cognitive Architectures, BICA 2016

Lose a leg but not your head – a cognitive extension of a biologically-inspired walking architecture

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Abstract

A cognitive extension for a behavior-based control system for a six-legged robot is proposed that allows a robot to deal with novel situations. Following a minimal cognitive systems approach a biological inspired control system is extended towards a system capable of planning ahead which utilizes a functional internal model of its own body in mental simulation. While the body model is grounded in the underlying control system it is also capable of prediction and allows therefore for internal simulation. An overview of the model and the process of internal simulation is presented. It is detailed using the example of leg loss in a six-legged robot.

Keywords: minimal cognitive system, emergence, internal model, mental simulation

Introduction

What makes a system a cognitive one? In order to approach this question, the proposed model follows a bottom-up approach and focusses on mechanisms that allow a system to become cognitive. As proposed by [7] cognition is understood as the ability to plan ahead. Following the basic assumptions of Embodied Cognition, a prerequisite for a cognitive system is that it is based on a reactive system and is embodied. Internal models play a crucial to allow for higher level cognitive abilities. The system should be able to not only select one of its behavior, but in addition, when experiencing a novel problematic situation, the system should be able to make an informed decision on different possibilities. This presupposes predictive internal representations which can be recruited [1] in an internal simulation [5]. Such a form of planning ahead is supported by findings showing the involvement of the motor system in cognitive tasks [6]. Importantly, such an approach requires the underlying representations to be flexible and grounded in the systems' interactions with the environment[2].

Selection and peer-review under responsibility of the Scientific Programme Committee of BICA 2016

doi:10.1016/j.procs.2016.07.412

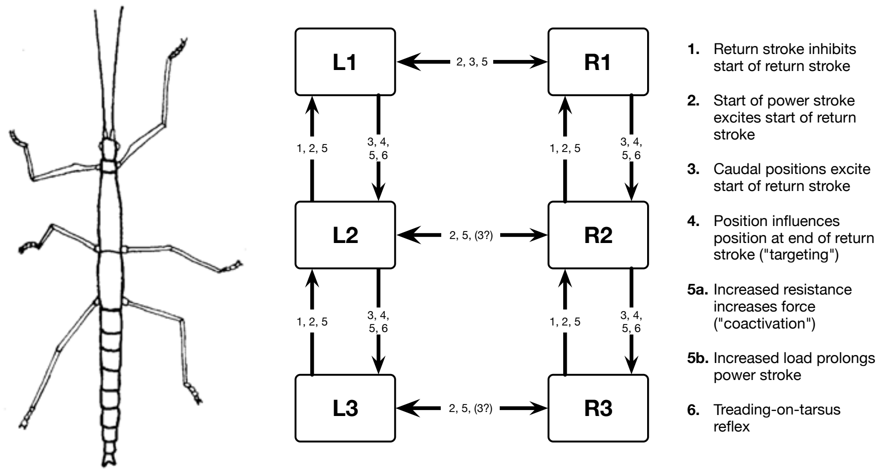

Figure 1: Schematic of the reactive Walknet control structure. The biologically inspired system consists of six controllers each responsible for action decision in a single leg (LF/RF left/right front leg, LM/RM left/right middle leg, LH/RH left/right hind leg). The walking behavior emerges from the interaction with the environment and is coordinated by coordination influences (left 1, 2, 3) that act between neighboring legs, prolonging or shortening the stance phase. Each leg controller contains several modules: a Swing-net and a Stance-net to control swing and stance movement, respectively.

ReaCog – a Minimal Cognitive System

An embodied approach will be presented which starts from a reactive control system called Walknet [10], summarized in fig. 1. The model is biologically inspired and mimics the behavior of the stick insect. As one crucial aspect, the overall complexity of control is broken down into local control modules (one is shown in the figure), one for each leg. These local controllers select which behavior to perform. Coordination rules act between neighboring controllers and produce overall stability of the system. This leads to emergent gaits also in challenging environments. The motion primitives themselves are realized as neural networks. Importantly, the control of the stance movements is very complex as it requires a coordinated movement of all the joints of the legs currently standing on the ground. This necessitates a form of internal representation mediating the overall movement. As a solution, an internal functional model of the body is applied [11] which is realized as a hierarchical recurrent neural network [9]. On the one hand, this model provides a solution for the inverse kinematics problem (a solution dealing with the dynamic properties of the movement is presented in [12]) as required for the control of the stance movement. On the other hand, the model is also predictive and can be used as a forward model [13].

These predictive capabilities of the body model are exploited to realize internal simulation. The behavior-based control model is extended in a way in which in novel, problematic situation, the model is testing variations of its behavioral repertoire out of the original context of the specific behaviors. As an example for illustration the loss of a middle leg will be used. The loss of a leg affects stability during walking and a new gait pattern is required in order to adapt. To overcome the problem, the system is able to flexibly adapt the coordination rules governing the

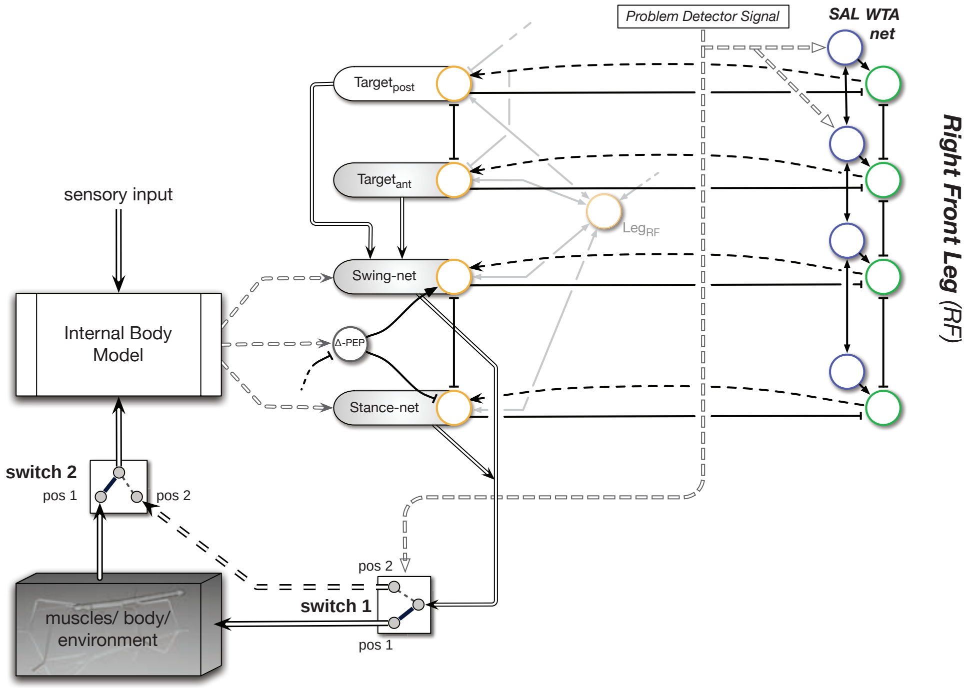

Figure 2: Expansion of the walknet control framework: an internal body model is introduced. During normal behavior, the Internal Body Model (upper left) serves perception. Switch 2 being in pos 1 provides proprioceptive input (e.g. joint angles from the legs). If the system runs into a problem, the body model is, together with the procedural networks, used for trying out variations of behavior. In this case both switches are flipped from position 1 to position 2 and the motor control (double-lined arrows entering switch I on the right) is routed not to the body anymore, but instead to the body model (dashed double line). This circuit is used for internal simulation and predicts the sensory consequences of the action. The units at the right (shown in blue and green) provide a structure for action selection during internal simulation. When a problem occurs an activation is spread in the first layer activating additional and close by units (blue layer). Only one of those should be tested in internal simulation. This selection is realized through a winner take all process (green units, activation of already in the current active behaviors is inhibited through the solid connections ending in the green unit).The whole process is repeated until a suitable behavior has been found.

overall walking behavior. But, as this is potentially further affecting stability, these changes and tests of coordination are not applied on the robotic system. Instead, they are applied in internal simulation. This requires an internal switch [5], decoupling the control system from the real system and instead routing the control signals towards the predictive internal model which provides predicted feedback. The feedback allows to decide if the applied change offers a solution for the current system.

Simulation of the extended approach have shown that in this way the model is able to find a new set of coordination rules that govern the walking behavior successfully and lead to stable walking again, even with a missing middle leg. The system is able to plan ahead and make informed decisions based on the predicted outcome for a given novel situation. Importantly, the extended system is exploiting the reactive control system as well as the already present and required predictive body model. Therefore, the cognitive capabilities do not require extensive novel structures and representation, but rest on the flexible use of the already present control system.

Related Work

There are two comparable approaches which both also deal with changes in the structure of a walking agent. First, in the approach by Bongard et al. [3] walking behaviors were learnt for a quadruped robot. In their case, learning consisted of two phases which were alternated. On the one hand, a body model was acquired through motor babbling. On the other hand, following an evolutionary training algorithm, a behavior for locomotion was generated utilizing the body model. A successful behavior was then applied again on the robot and the body model was adapted depending on the difference between expected and sensed feedback. The two different learning phases allowed to adapt to the loss of a leg or part of a leg. As an important difference, the used robot had only eight degrees of freedom and the approach would be problematic to scale up towards a problem as given for the hexapod case (which consists of 18 degrees of freedom).

Second, the recent approach by Cully et al. [4] also deals with an adaptive robot which can compensate for leg loss. In their case, possible walking behaviors are described through the coordination patterns of the six legs (meaning which legs are in swing at the same time). This lower dimensional behavioral space allows to enumerate all possible behaviors in a certain way. Crucially, for every possible behavior an optimization is found in advance following an evolutionary approach which is feasible as the selected specific behavior imposes constraints. After the loss of a leg, the behavioral space can be exploited as it already contains walking configurations during which one leg is not touching the ground at any time. As an important difference to the presented approach, this assumes fixed gait patterns which is not inline with biological findings on walking in general. Furthermore, it requires an exhaustive offline optimization which seems not suitable for even more challenging problems.

Outlook

The presented model is currently applied in dynamic simulation and to the six-legged robot Hector [8]. It will be used in different scenarios. First, the model shall be used to overcome unstable walking situations which might occur when walking through cluttered terrain. Second, it shall be applied to the loss of a single middle leg as briefly described here. In the future, the model will be extended to learn successful solutions to walking problems with respect to a given context.

Acknowledgements

This research/work was supported by the Cluster of Excellence Cognitive Interaction Technology 'CITEC' (EXC 277) at Bielefeld University, which is funded by the German Research Foundation (DFG).

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