Mechanical Cognitivization

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***Abstract*— The common approach for training robots is to expose them to different environmental scenarios, training their controllers to have the best possible commands when untrained scenarios are encountered. When humans train, they do the same. They try new manipulations by performing within different environments. However, humans training (and in fact development from infancy to maturity) also includes a type of training which, although claimed to improve cognitive capabilities, has not, to date, been adopted for the training of robots. This type of training involves the restriction of manipulation capabilities while performing different tasks, e.g., climbing with just one hand. The hereby reported upon research aims at exploring the invigorating idea that such training would enhance the robustness of robots and moreover may increase our understanding of why humans utilize such training in the first place. The main idea has been patented and is here published by a new name: Mechanical Cognitivization (MC).**

Keywords-cognitive robotics; developmental robotics; evolutionary algorithms.

I. INTRODUCTION

Robots are ubiquitous in performing industry related tasks and operating within hazardous environments. However, they scarcely participate in day to day tasks. In contrast, humans are those doing most of such jobs. The human competencies to perform arduous and complicated tasks while controlling and maneuvering a multi-degrees-of-freedom body are truly amazing. Through repeatedly executing different tasks, the human brain learns how to control the complex body.

Observing the humans' activities, two of them are of interest to the current research. The first is associated with sport related training. For example, while training, climbers often use different techniques such as climbing with one hand tied, without hands at all (on sloping walls) and blindfolded. Clearly, such situations are not envisaged in the actual climbing and are all training techniques that are intended to improve the climbers' sense of balance. Such restriction of movement, as a way to train, may be found in other sports (e.g., swimming, martial arts, and more). The other activity is also related to training under restricted movement, and involves the way human capabilities are developed from day one. Babies' brains are trained on a non-fully developed body. In contrast to calves, they cannot stand, walk or run. Yet, the evolution calls for such a slow development and compels using restricted capabilities. Maybe, this is due to the fact that in many situations, just some of the body's abilities need to be used and the body has to train also these sub-manipulations. It should be noted that in many sports, it is acknowledged that it is better to start young and let the body and mind adapt to the specific demands of that field of sport.

In contrast to the above, the major developments, as related to robots' learning and cognition were made with respect to the competencies of their artificial brains to learn, conceptualize, perform offline-planning based on anticipation and more [1]. However, these brains utilized fully developed bodies/embodiments. This is not to say that simultaneous evolution of solutions and their controllers were not investigated, but rather that such a development always considered one defined model for the body with a related controller [2].

The research proposed here suggests exploring the novel idea of enhancing the robustness of robots through training them while considering their final bodies/embodiments as well as their restricted-modes (less capable versions). It is contemplated that such training would enhance the robustness of robots to perform untrained maneuvers as well as to cope with malfunctions and unexpected working conditions. Moreover, such training is envisaged to be more optimally facilitated by specific bodies when compared to others. Therefore, optimization has to be incorporated. The basic idea has been patented [3].

In order to better elucidate the idea, suppose that a Robotic Climber (CR) that climbs on a wall that has poles sticking out of it, has to be developed. The left panel of Figure 1 depicts one possible mechanical configuration (body) for such a CR. The CR should now be trained to maneuver up and to grasp one of the poles (A or B).

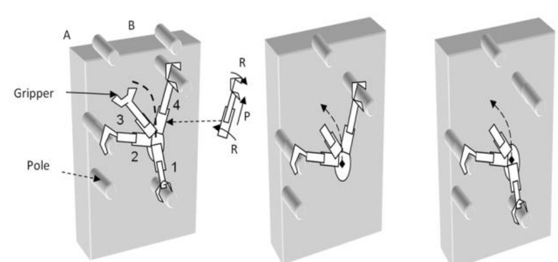

Figure 1: CR having four links is trained using all of them (left panel) and using restricted modes (middle and right panels).

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The idea suggested here is that while training this CR's controller, not only this body should be utilized, but also its restricted modes. Two of such restricted modes are depicted in the middle and right panels of the figure. Clearly, performing such a maneuver by utilizing one of the restricted modes might be associated with degraded performances (e.g., bigger integral of the square error, measured while considering the planned and the actual performed maneuver). Restricted modes may include the following restrictions: a. Using just some of its mechanical capabilities, such as restricting some of the links from moving, that is if the robot has four arms/links, it will be restricted to use three/two of them or not using its gripper, b. Restricting the movement of the arms/links to less than their full possible extent, c. Deliberately imposing friction at joints, d. Changing the stiffness of links, e. Restricting the performances of actuators, by for example: reducing the power supply to the actuators or using weaker actuators (smaller motors).

The paper is organized as follows. In Section II, the background for the current study is given. In Section III, a description of the already attained results is given. This is followed by Section IV, where a discussion and envisaged future work are given.

II. Background

Over the past several decades, a great deal of research attention has been directed at cognition and its implementation for artificial brains. The inspiration provided by human beings toward producing a machine that will copy human abilities is evident. Different models of cognition have been adopted to produce artificial cognitive systems or cognitive architectures. Cognitive architectures [1] represent attempts to create unified theories of cognition, i.e., theories that cover a broad range of cognitive issues, among them attention, memory, problem-solving, decision-making, learning. These theories consider several aspects, including psychology, neuroscience, and computer science. Examples of such architectures are EPIC [4], and ACT-R [5]. Some of these architectures have been claimed to be more adequate than others for use as cognitive brains for robots. This distinction [1], is rooted in the differences between the "cognitivist" and the "emergent" philosophies of cognition. The philosophy of emergent cognition contends that the relationship between the cognitive architecture and the body it is controlling (e.g., robots) is essential to the development of cognition. An associated philosophy is embodied cognition [6][7], which states that cognition can be influenced and biased by states of the body and that abstract cognitive states are grounded in states of the body. Among the architectures that facilitate this view is the biologically plausible brain-inspired neural-level cognitive architecture proposed by Shanahan [8], in which cognitive functions such as anticipation and planning are realized through internal simulation of interaction with the environment.

Several approaches have been proposed to improve the response of artificial entities to specific stimulations by circumventing complex cognitive architecture. For example, the computational model of perception and action for cognitive robots discussed by Haazebroek et al. [9] embraces the view that there is a direct route from perception to action that may bypass cognition [10]. A related approach is morphological computing [11][12][13], in which the idea is to design the mechanical structure to respond directly to a stimulus. This response is a result of the special morphology (shape, materials inter-relation among parts) of the structure. For example, in [14], the special features of a hand (Yoki hand) partially built from flexible deformable materials enable it to easily grasp different objects with no need for controller feedback. This notion has gained a great deal of interest, and for the past several years workshops have been dedicated to considering different aspects of morphological computing, such as artificial skin and stretchable sensors, compliant actuators and mechanisms, and soft materials in robotics.

Most relevant to the current paper are studies conducted by Mark Lee's group at Aberystwyth, UK. Their research is related to Developmental Robotics [15]. According to this approach, which is rooted in the way babies develop, cognitive development is achieved through staged growth of cognition as the sensomotoric competencies gradually and sequentially improve. In several publications [16][17] [18], Lee's group introduced and developed what they term as 'constraint lifting'. At each stage, learning takes place with certain constraints imposed on the sensomotoric system. At the next stage, some of these constraints are removed or 'lifted'. For example, learning hand-eye coordination in manipulating a robotic arm has been investigated. In that case, as learning progressed, constraints imposed on moving parts of the robot (e.g., using the fingers) were 'lifted'.

The proposed research focuses on the enhancement of cognition by considering the mechanical structure, as is the case in morphological computing. Here, however, the cognitive architecture is of vital importance, and the mechanical structure and its possible restricted modes (permutations of the final structure) are utilized for training the cognitive architecture. This means that the mechanical structure is the driving force for the enhancement of cognition. Moreover, the current project involves several basic differences from the works, such as [18]: a) In contrast to the sequential staged growth, MC may be enhanced simultaneously. b) In the proposed approach, constraining manipulations may take place any time along the robot's life time. c) In our research, a search for embodiments that will optimally benefit from the MC training will be conducted.

III. Promising Initial Results

Mathematical functions rather than a model of a CR were used to elucidate the concept of MC and to demonstrate its potential. A polynomial function Y(x) of order m, where x is a vector of inputs (e.g., location of poles), is used to represent the "environment" (the climbing wall) to which the CR must adapt (i.e., climb in the best way). In other words, Y(x) may be viewed as a planned route for the robot to follow. The CR's controller is a neural net (NN) whose outputs are the coefficients of a polynomial of order n, $y(x) = a_1 x^n + a_2 x^{n-1} + \ldots + a_n$. Each output may be viewed as a control signal (here a coefficient) to a motor of a manipulator that moves a robotic arm. By means of kinematics, the sum of the arm's movements results in the location of the CR on the wall, where the summing is represented by y(x). One way to enhance the training is to minimize the error, $Error = Y(x) - y(x)$. Figure 2 depicts the correlation between the CR case and the function representation.

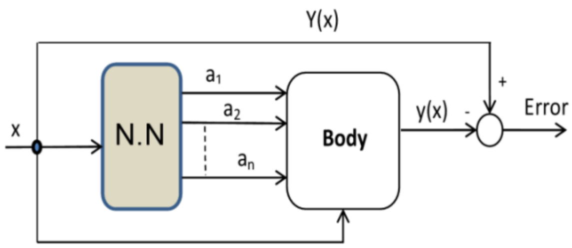

Figure 2. The correlation between the CR and the related function representation.

In order to train the net to provide output adequate to the environment (a function of order m), the artificial learning system is set, as depicted in Figure 3.

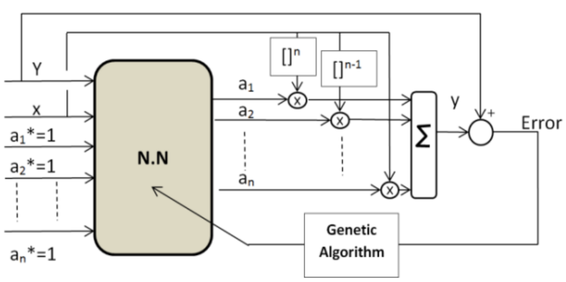

Figure 3. The artificial NN with no restricted modes.

The input to the NN is a list of K, x and corresponding Y(x) values that are fed sequentially to the net. The net has n extra inputs (flags), namely: $[a_1^*, a_2^*, ...a_n^*]$. These flags serve as the feedback to the controller and indicate the condition of related outputs. That is, if all outputs are functioning (no restriction of movement is associated with the manipulator's links), the value of the corresponding flag will be set to one, while if there is a restriction (unable to move due to a malfunction) a value of zero will be assigned to that flag. In the non-restricted training mode these flags are all set to one, indicating that no restriction is imposed on outputs and that all of them participate in estimating a function Y(x). A genetic algorithm was used to tune the net's weights so as to minimize the error. The results of the training are in the form of weights that for each input [x, Y(x)] produce a different set of outputs that best fit the target function Y(x). In the restricted mode, training the NN uses different sets of inputs, exploiting not more than the former system's available resources (K pairs). 1/n of the inputs, were pairs fed to the net together with all the flags, which were set to one as in the unrestricted mode. For the next 1/n inputs, the first output was prohibited and the corresponding flag was set to zero, as shown in Figure 4.

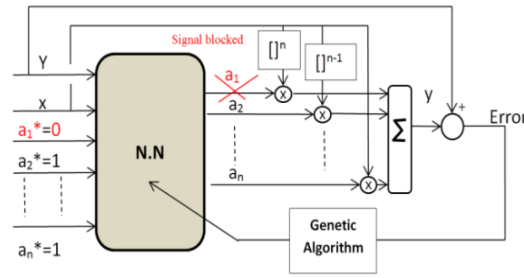

Figure 4. The artificial NN training setting for a restricted mode.

The implication of this training is that the weights are now trained to produce only n-1 outputs so as still to provide the best fit to the original function (environment). The other available resources were used to train the restricted modes by repeating this procedure for all other outputs while setting the corresponding flags to zero. In another version of this training, the available resources were divided among the restricted mode training such that more than one output was restricted. The left panel of Figure 5 depicts a target function as a dashed curve.

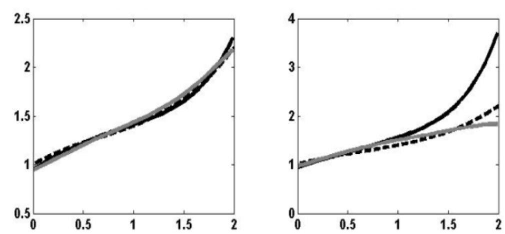

Figure 5. Left panel: The two NNs are trained to follow a function, right panel: Restricted mode shows better performances in following a function.

The trained non-restricted and restricted net outputs for a new arbitrary set of x points are shown in that panel by the black and the grey curves, respectively. Next, the performances of these differently trained entities have been compared while considering different scenarios: A. Malfunction in one or more of the outputs: In this scenario the environment is not altered (i.e., the same function has to be correlated) and the two different systems must still fit it. As stated in the patent, the MC-based system provides feedback that informs the net that there is a problem by setting the corresponding flag to zero. Because such situations have been included as part of the MC training, the performances of the related entity are expected to be superior. B. Environmental changes: In these scenarios, all flags are set to one (no malfunctions). This means that the two systems must perform in an untrained environment. A change in the environment is simulated by changing Y(x) by altering the coefficients (including setting one or several to zero) and the powers (not using only integers as powers). This is tested practically by entering a new set of inputs pairs (x, Y(x)) that corresponds to these changes. The right panel of Figure 5 depicts a common situation in which the MC approach showed merit. Here again, the target function, the non-restricted-mode trained function and the MC trained

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function are designated by dashed, black and grey curves, respectively.

These scenarios yielded the following observations: a) As expected, the superiority of the MC training was unquestionable for scenario A. b) For scenario B, no conclusive conclusions could be made, although as the n-m difference grew (possibly related to more degrees of freedom associated with the CR), the statistical success of the MC training became more profound. This observation clearly implies that, depending on possible environmental changes, some entities (order of n) will benefit more from MC training. c) If planning is taken into account, that is, if the different performances resulting from the different restricted-mode models are assessed before action is taken, the superiority of the MC is unquestionable. This means that at least one of the flags is deliberately set to zero, prohibiting at least one of the outputs so as to best fit the function at hand (the new environment). Thus, the CR may choose whether to use all of its arms in order to best fit the needed maneuver. A decision to deliberately prohibit movement may also be the result of failing to advance along a route and trying a different strategy for advancement.

IV. CONCLUSION AND FUTURE WORK

The suggested idea is to enhance the robustness of robots in performing within changing environments and tasks by optimizing and training them while exploiting their final mechanical configuration as well as their restricted mode configurations. Restricted modes are modes where part of the mechanical capabilities, are restricted. This means that such training should take into account multi-models (kinematics and dynamics) while training the entity to perform within different scenarios. The dependency of the controller's tuning, which may be related to cognition, on the mechanical structure and its related restricted modes, for the sake of inducing cognition, has been termed here as Mechanical cognitivization. For now, it seems that the success of the MC would be, for all scenarios, dependent upon optimizing the entity itself in order for it to fully exploit this type of training. It is noted that the main envisaged drawback of such optimized entities is that they will probably be more complicated and therefore will cost more. Although for the cases where planning is possible, success is more easily obtained.

As for future work, we intend to further exploit the use of functions in order to explore the fundamentals of MC optimization and training. However, due to the fact that the correlation between functions and robots is not always apparent, the idea will be examined through evolving embodiments and simulating their performances within artificial environments. More futuristic plans include testing the MC by using learning by demonstrations and more.

V. ACKNOWLEDGMENTS

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