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Brain-inspired self-organizing modular structure to control human-like movements based on primitive motion identification

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ABSTRACT

In this paper we will propose a modular structure to control the human-like movements of a robot in a way similar to which human brain does to perform the motor control. Modeling of human motor control and motor learning has attracted researchers' attention in robotics and artificial intelligence for decades. It is obvious that discovering the motor control functionality of brain as the most complex, sophisticated and powerful information-processing device leads to significant advancements in robots movement. Hence, our proposed modular controller is based on human brain behavior in using neural mechanisms named internal models and primitive motion identification which leads to extract and learn the latent simple motions in order to imitate observed complex movements. The study is accomplished based on formerly proposed structure, MOSAIC, which provides remarkable efficiency in motor control modeling. Examination of the proposed structure with real recorded data, confirms the performance of the controller in learning and executing motion tasks.

1. Introduction

Researches have confirmed that human motions are produced by combination of primitive motions. The primitive motions are simple and atomic movements which sequences of them form complex motions [1]. Therefore, identification and learning of primitive motions, got attentions in various fields of study. In the case of artificial intelligence and robotics, learning of primitive motions for performing complex movements, reduces the computational cost of motion planning and control. This is because of transforming the large space of joint data into relatively small space of primitive motions. On the other hand, dedicating a simple controller to each primitive motion yields dealing with easily implementable control approaches [2].

Furthermore, studies on human motor system show that a set of special neurons named Mirror Neurons, play an important role in coding primitive motions for motor learning system [3,4]. These neurons are primary elements in representing imitation capability by human. In other words, they are known as the mechanisms of imitative learning. However, a big question in biology and cognitive sciences is “how mirror neurons can do that?” Associative Sequence Learning (ASL) theory for imitation can provide acceptable answer for that [5]. According to ASL theory, motion learning is accomplished based on motion units. These units are indeed the constitutive segments of the observed movement. However, learning is performed through two different processes related to sensory system and motor system, which are executed in an associative manner.

Researchers believe that, there are another neural mechanisms beside the mirror neurons which provide the ability of executing the observed motion [6]. These mechanisms are stated as Internal Models. Internal models are neural based structures that model the input/output relationship for sensory–motor system. There are two types of internal models: *Forward internal models* which can predict the sensory measurable output of the motor system regarding to motor commands while *Inverse internal models* receive desired state information to generate motor commands in a feedforward manner. In other words, human brain utilizes several forward internal models as state estimators to predict the next state of the system and the inverse internal models as feedforward controllers to produce motor commands [7].

Using internal models by brain, humans can learn the dynamics of the motor system and amend their intrinsic knowledge about the characteristics of the sensory–motor system while growing up. Therefore, they can improve the motions from infant period on, by

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executing the movements repeatedly. This capability is stated as Active Intermodal Mapping (AIM) theory [8]. According to AIM theory, human infant exploits the inherent ability of mapping the perception and the execution of movements.

Additionally, scientists believe that most of imitative behaviors are justified by higher level mechanisms [9]. It means that, imitation by human occurs not in execution level but in planning step. Therefore, imitation is used to learn the optimal form of the observed motion. The optimality is defined based on self-knowledge of sensory motor system which is obtained via internal models. Accordingly, GOAl-Directed Imitation (GOADI) theory represents that, imitation is a facility to achieve the goals and sub-goals specified by the human perception [10]. Regarding to GOADI theory, human does not copy and paste the observed motion, but he tries to extract the sub-goals which are latent in the observed movement. These sub-goals are then learnt and accomplished by human motor system.

The unity between three discussed theories, ASL, AIM and GOADI, eventuates that the learning and control of complex movements through imitation, is performed by learning and control of constitutive primitive motions via forward and inverse internal models. Therefore, implementation of well designed mechanisms on robots for learning and control of primitive motions through movement observation, facilitates motor learning while providing the human-like motion planning and perception capability [1,11].

One of control strategies which was proposed based on internal models theory, belongs to Wolpert and Kawato [12]. Their proposed structure is a modular architecture which later they named it MOSAIC (MOdular Selection And Identification for Control). MOSAIC is a computational model to solve two major problems simultaneously: the learning of modules and the selection of them. The fundamental concept is to use multiple inverse models as controller, each of them coupled with a dedicated forward model. The key point is benefiting from responsibility signals which specify the responsibility of the modules to take the action throughout confronting conditions. This signal is generated using the prediction from every forward model and calculating prediction errors during the movement to identify the encountered dynamic or kinematic condition. While coupling forward and inverse models, the responsibility signal takes the main role in learning of models and determining the portion of each module to perform the control action. The major benefit of MOSAIC is to control a dynamic model in a modular way which provides simultaneous learning and execution. It means while some modules attempt to learn new motions, the others can carry out the previously learnt actions with no interference.

Despite the capabilities of original MOSAIC in modeling of human brain functionality in motor control and also biological plausibility as one of its remarkable properties, there are some considerations to improve the computational model and make it perform as much similar as possible to human brain. Since the original paper on MOSAIC [12], a few extensions have been proposed. By using Hidden Markov Model, HMM–MOSAIC [13] could improve the switching between modules. In this model, a specific type of Expectation Maximization is used as module learning algorithm. Although the probabilistic structure of HMM–MOSAIC is not compatible with biological facts, the authors believe that it outperforms the original MOSAIC in identifying and distinguishing different dynamic conditions. The MOSAIC was later extended to a hierarchical structure, HMOSAIC [14]. In this cascade architecture, the higher-level MOSAIC is provided with desired trajectory and actual responsibility signals from modules in lower levels to predict the responsibilities of its subordinate modules in order to accelerate module switching. Another extension of MOSAIC, eMOSAIC, is proposed in [15] to control a humanoid robot in nonlinear and nonstationary conditions. eMOSAIC uses Kalman filters instead of forward models as state estimators. Moreover, coupling a Liner Quadratic controller with each state estimator, makes every module perform as a Linear Quadratic Gaussian controller. Nevertheless, eMOSAIC has invariant structure with no adaptation capability. AMA-MOSAICI is another version of MOSAIC which was used to control the movement of a simplified human body skeletal model [16]. The structure contains a preprocessing step to decompose the movement using a linear clustering algorithm. Subsequently, each part of the movement is dedicated to one module to learn and execute in a predefined way. However, both the clustering and module dedicating steps are performed in offline manner.

Each of mentioned extensions has attempted to solve an important problem and improve the functionality of MOSAIC in different aspects. Yet, a significant questions is left with no answer. The problem is how to define the optimal number of modules for MOSAIC autonomously, within performing a certain task. It is clear that, for a modular structure the wrong number of modules affects the performance of the controller. Hence, inadequate number of modules yields to large performance errors and in some cases improper response time, while extra module exploitation increases computational costs. Although, the two recent extensions, eMOSAIC and AMA-MOSAICI, have considered the problem of modules number, but the adopted methods are not consistent with biological facts about the human brain functionality. In eMOSAIC, the optimal number of modules is defined through a trial and error approach. Therefore, a certain task is controlled using different number of modules in the structure within several experiments. The optimal number of modules is then obtained based on minimizing a predefined cost function. On the other hand, AMA-MOSAICI defines the required number of modules by preprocessing the given task in an offline manner before task execution. The preprocessing includes decomposing the movement into several parts and defining the modules number equal to the movement parts quantity. Since it is supposed for MOSAIC and its extensions to model the human brain in motor control, both methods adopted by eMOSAIC and AMA-MOSAICI are not biologically plausible.

Therefore, in this paper we will propose a modular structure based on MOSAIC which can reform its structure incrementally and according to the task complexity during execution of observed movement in an online manner. Hence, the structure can define the optimal number of modules autonomously without any predefinition. For this purpose, an online approach is employed to identify the latent primitive motions within the observed movement and decide whether to create a new module or not based on similarity between identified primitive motions. Thus, our proposed structure embraces the three mentioned theories, ASL, AIM and GOADI and by using the strength points of MOSAIC outperforms the other extensions in modeling the human brain functionality for motor control.

The rest of the paper is organized as follows. In Section 2, we will introduce an online segmentation algorithm which we have used to identify constitutive primitive motions of a complex movement. Section 3 is dedicated to express our proposed modular structure, based on MOSAIC with primitive motion identification. The structure is then tested to control a body-skeletal model to imitate the movement of rising from chair by a healthy subject via recorded data and the results are represented in Section 4. In Section 5, we give some conclusions and discussions about the superiorities of our proposed structure.The paper is closed by discussing our future works in Section 6.