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AMA-MOSAICI: An automatic module assigning hierarchical structure to control human motion based on movement decomposition

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ABSTRACT

In this study, a hierarchical structure is proposed to model human movement control during sit-to-stand transfer. At the highest level the desired movement is planned. Then, the task to be performed is decomposed to its constitutive sub-tasks. To decompose the sit-to-stand movement, the spatial trajectory of the body center of mass is automatically approximated by partially linearized trajectories. Each linearized part defines a sub-task. At the second level, corresponding to each sub-task a module is developed that learns to control the movement during the performance of that sub-task. Since the procedure of decomposition is performed automatically, the number of modules and assessment of suitable data to train the modules are also determined automatically. This feature is one of the main differences between the proposed structure and the MOdular Selection And Identification for Control (MOSAIC) structure [M. Haruno, D.M. Wolpert, M. Kawato, MOSAIC model for sensorimotor learning and control, Neural Computation 13 (2001) 2201–2220.]. Our proposed model is in conformity with the recent physiological and neurobehavioral findings and provides a framework for examining a given movement under different conditions.

1. Introduction

Several models in literature have been proposed to describe how the central nervous system (CNS) controls human movement. Different points of view were used in developing human movement control models.

One main group of these models is based on development of internal models of the motor system in interaction with its environment, in the CNS [6,30,13]. The internal models are either the inverse or the forward models [4,30,23,24,29,39,38,42,43]. Based on the mentioned point of view, control variables are muscle forces or joint torques [4,30,23]. Later, more complicated controllers including both inverse and forward models were developed [4]. Recently, it has been suggested that the CNS as a controller has a modular structure so that each module consists of an inverse and a forward internal model among other components [30,23,29].

Internal forward dynamic models predict the actual state of the system and the corresponding sensory information based on the actual motor commands and the previous states of the movement. The discrepancy between the predicted and the actual sensory feedback information results in an error signal. Physiologically, this error signal might be calculated in inferior olive [2]. This signal is used to adjust or train the forward model, which most probably is located in the cerebellum; it is also used to correct the motor commands [2]. Wolpert and Ghahramani [5] proposed a structure containing several forward internal models to improve the effectiveness of the context estimation model; each forward internal model predicts sensory information to compensate the delay of actual sensory feedback.

Internal inverse dynamic model predicts desired motor commands based on the current movement states and the next desired ones. Actual movement is compared with the desired one and thus an error signal is produced. This signal is applied to train the inverse model and to correct the motor commands [6].

Sensory information feedback signals lag behind the motor commands. Despite this, CNS controls the limb movement skillfully and accurately. Therefore, human motor control system is not based entirely on feedback signals; CNS uses feedforward control also [40].

Wang et al. [46] proposed a model based on simultaneous development of both forward and inverse internal models in CNS. In this structure the internal forward model predicts sensory information and the internal inverse model predicts suitable motor commands. The prediction of the sensory information compensates for the undesired effects of delay in the sensory information.

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At the same period of time, Haruno et al. [30] proposed a modular structure to describe human movement control system and later in 2003 they developed a hierarchical structure based on the same modular model. Modular structure controllers have been proposed to decompose the control of a complex task into constructive sub-tasks. In this case, the control of the task is accomplished more robustly [29]. In the modular structure each module contains both inverse dynamic (called control model) and forward dynamic (called predictor model) models. Considering its structure, Haruno et al. [30] called it the model MOdular Selection And Identification for Control (MOSAIC). Each module of the MOSAIC learns to control the movement of the body for a given sequence of tasks/conditions. Each module contributes to the generation of the motor command according to its corresponding responsibility. This responsibility is determined based on the likelihood of the output of the predictor model and the next desired state of the movement. Multi-layer perceptron (MLP) neural networks were used to simulate inverse and forward dynamic models in different modules. Haruno et al. [30] applied teacher forcing [41,24] technique to train the modules. In the teacher forcing method, instead of the actual output which is not practically available, the desired output (the state of the motor system) is used to train the networks. The modules after being trained offline have assumed their function in the whole system, separately. The number of the modules of MOSAIC is predetermined or, in other words, specified manually [29]. As Haruno and colleagues showed, the structure was robust against noise in intrinsic parameters (such as anthropometric parameters) and external disturbances. They have discussed physiological evidences to validate the MOSAIC model.

Although, most probably, a suitable model to describe the control of a complex task by human motor system should have a modular structure [30,29], there are still some important questions to be answered. How does the CNS determine the suitable number of modules? How are suitable data specified for training the modules? In this article, we propose a new approach to study these problems.

Based on physiological evidences [33,12,2] a hierarchical structure with three levels has been considered for the motor control system, which are motor planning, motor programming, and motor execution. In the first level, the plan of the movement is generated; then at the programming level the movement is programmed, that is motor commands are determined, and then at the third level these commands are applied to the musculoskeletal system. These levels may constantly interact during task performance; for instance, some researchers have stated that the human motor system can update a planned movement in the presence of external disturbances that produce unanticipated changes in position, velocity, and visual properties of the target [3,45,7,18]. However, we assumed that the conditions of task performance do not demand the preplanned trajectory to be modified by CNS during task performance. The same assumption has been used implicitly by many other researchers (e.g. [4,34,30]).

In this work, we used a model previously proposed by our group to generate the desired movement in the joint space [28]. In the proposed structure it was assumed that movement planning is accomplished by a supervised imitation. The planned movement at this stage was used to decompose the movement space into several clusters and also as the reference input for the controller. We used the generated movements also to train different modules during simulation process.

For motor programming level, we proposed a hierarchical structure inspired by the original MOSAIC model to simulate the human motor control system during STS transfer from a chair. We named this structure automatic module assigning MOSAIC-inspired (AMA-MOSAICI) model. In the original MOSAIC the sub-tasks are in fact the same task performed with different loads (changes in environment). In this study, we decomposed a unique task into sub-tasks, which are in fact performed in a serial order. Thus, each module cooperates in controlling one sub-task that is a part of the main task. To decompose the task autonomously, we proposed a method to divide STS into its sub-tasks based on behavioral data. In this case, to obtain the suitable number of modules and suitable sequences of the data to train each module, data presented for task performance are divided into four clusters (sub-tasks) at a level higher than the control level.

To obtain a suitable criterion to decompose the task into sub-tasks we used uncontrolled manifold (UCM) analysis. Scholz and Schöner [20] gave an operational meaning to “controlled” and “uncontrolled” variables and introduced a method of analysis of controlled and uncontrolled degrees of freedom. In this method, variations of the changes of the candidate variable relative to changes of the joint angles are projected on to the movement manifold ($||UCM$) and the manifold perpendicular to it ($\perp UCM$), respectively. Then, the ratio $||UCM/\perp UCM$ is calculated. This value is an indicator of the importance of the candidate variable for the control of the task. According to the results of UCM analysis, the body center of mass (COM) is one of the variables that is most probably controlled by CNS during STS transfer [20].

This observation is in accordance with the results of Mataric and Pomplun [31]. They have concluded in their study that the specification of a movement task is most probably given by the trajectory of the end point of the system. Now one can consider the body COM as the actual end point of the body during STS transfer and the horizontal and vertical trajectories (time histories) of the body COM as the end-point variables that carry information about the STS transfer task.

Driven by this idea, we decomposed the STS task into different classes using the spatial trajectory of the body COM; decomposition is applied by partially linearized approximation of the spatial trajectory of the COM. Each class will represent a sub-task of the movement. The data corresponding to each class are determined and later used separately to train the corresponding module. The data used to train the modules were joint angles, angular velocities of the joints, and joint torques.

In the structure of AMA-MOSAICI, we assumed that the necessary number of modules is equal to the number of classes. Therefore, we used the data of each class to train its corresponding module. This means that the number of modules and the data for training those modules were specified automatically. The training data for the modules are joint angles, joint torques, and angular velocity of the joints. As a case study, we chose the sit-to-stand (STS) transfer from a chair, because, as will be discussed later, evidence indicates that the STS has separate phases [37] or in other words, it consists of several sub-tasks. In addition, this task is more complex than the reaching movement, which was often used in previous researches [30]. Our results showed that four modules were sufficient to control the STS movement. These four modules correspond to the four phases of STS movement mentioned by Riley et al. [37], that is, flexion momentum phase, momentum transfer phase, extension phase, and finally the stabilization phase. We used linear networks as forward and inverse dynamic models in the structure of the AMA-MOSAICI. The learning method used to train the internal inverse and forward dynamic models of each module was supervised learning; we also used teacher forcing technique to train the modules.

The paper is organized as follows. In Section 2, the general architecture is introduced. We will show how movement patterns can be generated by supervised imitation and will also explain how the number of constitutive controllers (modules) is determined automatically. Then, in Section 3, the simulation results for