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The Use of Artificial Neural Networks in the Motor Program

Wu Ping[1, 3], Bao Jia-li[1]*, Xia Qiang[1], I. C. Bruce[2]
1 College of Medicine, Zhejiang University, Hangzhou 310006, China
2 Department of Physiology, University of Hong Kong, China
3 School of Medicine, Hangzhou Teachers' College, 310031, China
* Corresponding author, Email: baojl@mail.hz.zj.cn, Tel: 86-571-87217390

Abstract—**Though it is commonly assumed that the brain creates "motor programs" which store the information essential to perform a motor skill, little direct evidence exists for such motor programs. Electromyography (EMG) provides a look into the motoneurons – level of a movement by measuring the electrical activity in relation to the muscle's involvement in the movement. In this paper, artificial neural networks (ANNs) were applied to define the temporal patterns of EMG activity used by normal subjects in performing step-tracking tasks, and how such patterns change with practice. Our results demonstrate that ANNs could be trained to detect the input-output relationship between muscles' onset times and reaction times, and provided evidence to support the existence of a motor program.**

Keywords— **Electromyography (EMG), motor program, artificial neural networks (ANNs)**

I. Introduction

Since the late 1960s, a central concept in the control of voluntary movement is that the brain generates some kind of algorithm (motor program) that results in a movement. The algorithm specifies at least: [1][2][5][6][7]

1) Which muscles will be turned on, which muscles will be turned off, and which muscles will be ignored (there are about 600 muscles in the human body).

2) When each muscle will be turned on (EMG onset times).

3) How much each muscle will be turned on (EMG amplitude/area).

4) When each muscle will be turned off (EMG offset time).

From an engineer's point of view, it's like simultaneously controlling up to 600 torque motors to produce precise forces acting on linked levers.

But there is still no published evidence that motor programs exist. Most workers measure biomechanical variables, like reaction time and interpret their results in terms of the motor program. Some workers measure EMG onset/offset/amplitude from no more than 2, usually antagonistic muscles, which is useless in terms of identifying a central algorithm or pattern. They restrict themselves to 2 or 4 muscles because, until recently, the permutations and combinations quickly make analysis impossible.[3][4]

We attempt to apply ANNs to simultaneous recordings from significant numbers of muscles (=8) to recognize patterns in EMG onset times, i.e. features of the central algorithm, if it exists. Our strategy is that an ANN trained on data from a learned task can be used as a probe to investigate differences between the learned pattern and patterns generated during the learning process.

II. Methods

A. Multi-layer Perceptrons (MLPs) Neural Network

A commercially available simulator software package (NeuroSolutions Version 4.0: NeuroDimension, Inc., USA) was used to construct the neural networks.

Multilayer perceptrons (MLPs) are layered feedforward networks typically trained with static backpropagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map.

The MLP neural network topology of three layers; an input layer, an output layer and a hidden layer with 8 processing elements (PEs) was chosen for this study (Fig.1). The 8 EMG onset times provided the input to the network, while the measured reaction time (RT) was the desired output for the network. The error between the predicted output from the network and the desired output would be minimized based on backpropagation rule. The training continued until the error reached the stop criterion of 0.01%. The hyperbolic tangent function was the activation function. The maximum number of epoch was 1000. The training rate of the batch method was chosen for this study.

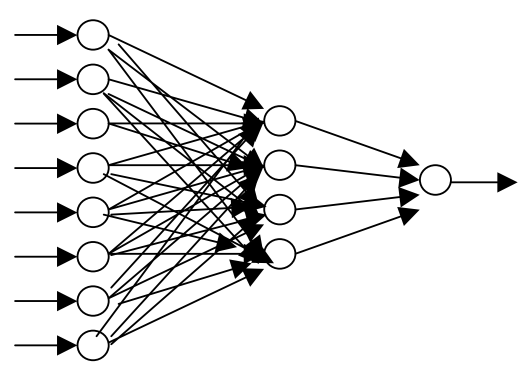

Fig. 1 MLP neural network topology

B. Data Acquisition

15 healthy, right-handed volunteers (7 men and 8 women, aged 25-42 years, mean 29 yrs) participated in the experiment. They were all naïve with regard to the specific purposes of this study. The Ethics Committee of the University of Hong Kong approved all experimental procedures (EC 827-96).

Each participant was seated comfortably in a dental chair, with the forearms resting on an adjustable support. An individually fitted thermoplastic cast held the forearm stable, in order to maintain the same elbow, wrist and hand posture over the recording period. The participant was asked to use their left hand to grasp the handle of a manipulator mounted on a sturdy platform. The manipulator handle rotated freely around a bearing centered on the axis of rotation of the wrist. A potentiometer coupled to the bearing gave a continuous measure of wrist angle and its output was digitized and stored. Surface electrode pairs were placed about 1 cm apart on the skin overlying the following muscles: Abductor Digiti Quinti (ADQ), Abductor Pollicis Brevis (APB), First Dorsal Interosseous (FDI), Flexor Carpi Radialis (FCR), Flexor Carpi Ulnaris (FCU), Extensor Carpi Radialis (ECR), Extensor Carpi Ulnaris (ECU) and Extensor Digitorum Communis (EDC).

An oscilloscope screen displayed a cursor and a target in front of the participant. The cursor was a horizontal trace that moved in proportion to the wrist movements. It moved upwards for wrist extension, while moving downwards for wrist flexion. The target was a horizontal trace, which also moved in the vertical axis. The location of the target on the screen was determined by the computer.

To initiate a trail, the participant superimposed the cursor line on the target line and maintained this position until any observable target movement. The target then jumped instantaneously to a new position. The participant was required to move the cursor, as accurately, and as fast as possible, to this new position. After 500 ms, the target then moved instantaneously back to the initial position, and the participant was asked to move the cursor to follow the target movement, as accurately, and as fast as possible, back to the initial position, where the target remained for 500 ms. Thus each step was 1 second in duration. The process was then repeated 75 times in 75 seconds. No practice trails were allowed.

While the participant performed the step-tracking movements, signals from the potentiometer and the 8 EMGs were stored in computer memory for further analysis. The raw EMG signals were amplified (×1000) and band-pass filtered (30-1000 Hz) using conventional preamplifiers (Model P15, Grass Instruments), and then digitized with 12-bit resolution at a sampling rate of 1000 Hz (DT21EZ, Data Translation Inc.).

III. Results

Fig.2 describes performance measures of movement, including:

1) RT (reaction time): the difference between the time the target moved and the time the subject began to move the wrist. A positive value indicates the subject moved after the target began to move; negative means the subject anticipated the target movement. RT has been used as the classic measure of motor learning in millions of experiments since the 1860s. RT decreases with practice. RT consists of PRT (premotor reaction time) and MRT (motor reaction time).

2) MT (movement time): the time from the beginning of the wrist movement until its end. Probably not important, but also tends to decrease with practice.

3) PRT (premotor reaction time): the time from the onset of the target movement to the first detectable EMG change of the prime mover (the principal muscle producing a movement, FCR is the prime mover in this trial).

4) MRT (motor reaction time): the time from the first detectable EMG of the prime mover to the onset of the cursor movement.

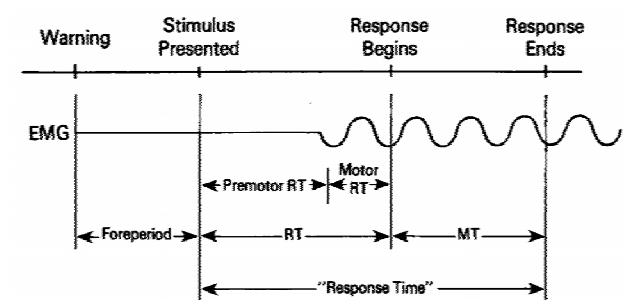

Fig. 2 Schematic diagram shows RT, MT, PRT and MRT.

Fig. 3 shows the first few trials of a typical experiment. The square wave on the bottom (blue) trace represents the target that the subject is trying to track by flexing and extending the wrist. The superimposed trace (pink) shows the actual wrist angle; in this case the subject fails to follow the first three trials and then starts tracking. The eight upper traces show the rectified EMG signals from wrist and hand muscles.

The MLP neural networks constructed in this study had the capability to 'learn' the input-output relationship between the EMG onset times and the reaction time within the criterion we set for the network. These results demonstrate that there is a very strong relationship between the 8 EMGs' onset times and RT.

Other different types of neural networks were also tried to train the data. Self-organizing feature map network (SOM) had the ability as well. The feature maps are computed using Kohonen unsupervised learning. The output of the SOFM can be used as input to a supervised classification neural network such as the MLP.

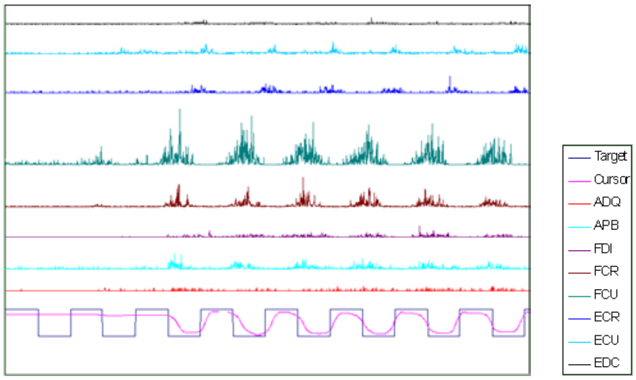

Fig. 3 Activity profiles of all the 8 muscles recorded in the first 8 steps for subject A. The EMGs are full wave rectified.[9]

IV. Discussion

Researchers from different fields of study, such as experimental psychology, motor behavior and neurobiology, have provided evidence to support the existence of motor program. Other than theoretical issues raised by the idea of motor programs, another more pragmatic line of research is aimed at identifying the content and structure of such programs. [1][3][5][8] But the problem is there is still no consensus on what constitutes a motor program. The main reason is because of limitations of the technology available to previous studies. For example, the acquisition and analysis of many channels of complex data continues to pose a major challenge. The use of ANNs in this study is a new approach to investigate motor programs.

EMG data provide an indirect, but perhaps the best indication of the timing of exerted force and relative changes in force produced during movement. More significantly, it also tells us about instructions arriving at the motor neurons from central control center. One way to study motor learning is to measure the spatial and temporal patterns in the muscles' activation (i.e. EMG) pattern. In this study, the temporal patterns in the muscles studied were the point of focus. Unlike previous studies, we were interested in observing the changes in the activation patterns of all 8 muscles rather than an individual muscle and its antagonist, because joint movements depend on more than one muscle.

ANNs is proved effective for the study of motor program. We can further apply them to more parameters (PRT, MRT, MT, amplitude of EMG, frequency spectrum of EMG, etc.) to obtain more evidences for the existence of motor program and its characteristics.

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