Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Toward Filtering of Athetoid Motion with Neural Networks

Juan J. Vázquez López, Sara Sibenaller, Dan Ding, *Member, IEEE*, and Cameron N. Riviere, *Member, IEEE*

***Abstract*—People with athetoid cerebral palsy (CP) have difficulty using computers due to unintentional involuntary movements in the upper extremities. A neural network-based system has been developed to cancel the undesired motion, and speed up the movements and accuracy in target acquisition and path tracking tasks while using an isometric joystick (IJ). Nonlinear filtering algorithms were created with neural networks using nonlinear models to help people with athetoid CP to access the computer. This paper presents unfiltered test data that have been collected from patients, and describes the planned filtering approach.**

I. Introduction

Athetosis, a complex movement disorder that appears in 10-20 percent of persons with CP, has been described as a slow, wormlike, writhing motion, which obstructs purposeful movement and is found mainly in the upper limbs [1, 2]. Athetoid movement is irregular and difficult to predict because it lacks a fixed amplitude, rhythmicity, and direction [3]. People with moderate cases of athetosis find using personal computers, power wheelchairs, and other devices difficult, while those with severe cases are often unable to use them at all, because purposeful movements are completely masked by the involuntary motion [4]. Therefore, athetosis creates an added complexity for developers of assistive technology.

Current interface solutions for athetosis have significant drawbacks. One common approach is to develop interfaces with sufficiently low bandwidth and input gain that users with athetoid motion are capable of controlling them. In other words, the task is simply slowed down until the user can accomplish it successfully. Users with the most severe cases of athetosis are limited to the use of a single-switch interface to control a computer. This is often combined with scanning software, in which a set of characters or symbols is highlighted in sequence, each being dwelt on long enough to allow the user to click and choose it if desired [5]. Another approach is to develop interfaces to be controlled with different body parts, which may exhibit less athetosis than the arm and hand.

However, use of the arm is more natural, and would therefore be preferable if effective filtering were available. Linear filtering of joystick signals is of limited benefit, since athetosis not only reduces the bandwidth of purposeful movement, but also corrupts the remaining bandwidth with involuntary motion at the same frequencies. As a result, the investigators have recently begun to develop filtering algorithms based on nonlinear models of athetoid movement, to be used in conjunction with an isometric (force sensing) joystick (IJ) to enable computer access for people with athetoid cerebral palsy (CP). The isometric joystick (IJ) used in this study, developed by researchers at the Human Engineering Research Laboratories (HERL) in Pittsburgh, PA [6], is helpful for cases of athetosis because the involuntary motion rapidly saturates position-sensing joysticks. The goal of the present research is to enable persons with athetosis to use computers, some for the first time, others more easily and effectively than before. The algorithms developed in this project will be useful not only for personal computers, but also for powered wheelchairs and similar devices [7].

This paper quantifies the unassisted performance of three athetoid subjects in icon-clicking trials and describes the planned filtering approach.

II. Methods

A. Target acquisition trials

To obtain data for filter development, target acquisition (icon-clicking) tests using the IJ were conducted at HERL with three subjects with athetoid CP. Signed consent was

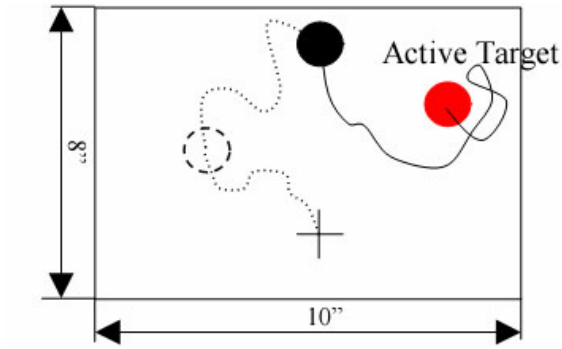

Fig. 1. Scenario for trials. At the start of each trial the cursor appears at a random start point, marked by a circle. At the same time, a target circle appears. The subject is told to move the cursor to the target circle and to indicate a "click" by dwelling inside the target for 2 s.

Manuscript received June 22, 2007. This work was supported in part by the NIH under Grant R21 HD050717, and the University of Valladolid.

J. J. Vázquez López is with the University of Valladolid, Spain.

D. Ding and S. Sibenaller are with the University of Pittsburgh, Pittsburgh, PA 15260, and Human Engineering Research Laboratories, VA Pittsburgh Healthcare System, Pittsburgh, PA 15206 (phone: 412-365-4850; fax: 412-365-3858; email: dad5@pitt.edu, sibenallers@herlpitt.org).

C. N. Riviere is with the Robotics Institute, Carnegie Mellon University, Pittsburgh, PA 15213 USA (phone: 412-268-3083; fax: 412-268-7350; email: camr@ri.cmu.edu).

provided under a board-approved protocol. The task performed by the subjects is depicted in Fig. 1. The locations of starting points and target icons were random within a 25×20-cm rectangle on the screen. The target icons were circles 2.5 cm in diameter. (For the second subject, the original target diameter had to be doubled to enable successful completion of the experiment, because of the severity of the athetosis.) The distance from starting point to target icon was random. In order to select a target, subjects were instructed to dwell on it with the cursor for 2 s. A trial was recorded as a failure if the target was not acquired within 20 s.

Each subject performed ten sets of ten target acquisition trials, for a total of 100 trials. Data were sampled at 100 Hz. The cursor position and the raw output signals from the joystick were recorded and used to develop the neural network model.

B. Nonlinear filtering

A neural network has been selected to implement the desired nonlinear filtering. For maximum versatility, instead of a traditional multilayer neural network design, we have chosen the cascade-correlation architecture (Fig. 2), a constructive neural-network technique, first presented by Fahlman and Lebiere [8] and expanded by Nechyba [9], which has seen previous use in filtering of erroneous movement [10]. The technique involves dynamic adjustment of the size of the neural network as part of the learning process. Cascade-correlation begins with a minimal network, then automatically adds and trains new hidden units one by one, creating a multi-layer structure.

Once a new hidden unit has been added to the network, its input-side weights are frozen. This unit then becomes a permanent feature-detector in the network, available for producing outputs or for creating other, more complex feature detectors. The cascade-correlation architecture has several advantages over a fixed multi-layer architecture: it learns quickly, the network determines its own size and topology, and it has been shown to outperform multilayer networks with backpropagation in similar applications [9].

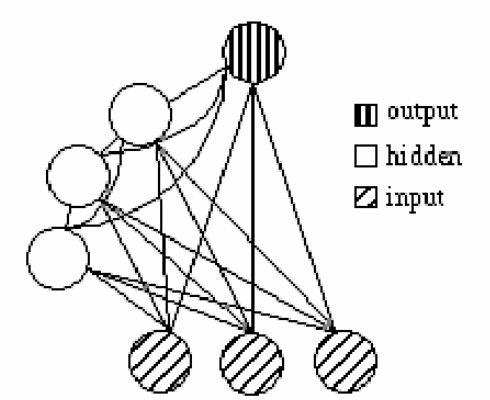

Fig. 2. Structure of a cascade-correlation network. As each hidden node is added, it receives connections from all the inputs, and from all the preceding hidden nodes.

In this project the Levenberg-Marquardt algorithm [11, 12] is used to train the network.

The planned filtering approach involves training two separate neural networks, one for the *X* axis and the other for the *Y* axis, as shown in Fig. 3. A separate *X*-*Y* pair of neural networks is trained for each test subject. The networks use the velocity in each axis as input, so that the trained result is independent of the absolute position of the cursor on the screen. Of the 100 trials from each subject, the first 50 trials are used to train the networks. The remaining 50 trials are used as a testing set. This is done in preparation for the true test of the system, which of course will be online validation of the trained system in a second experiment with the human user.

Improving the accuracy or smoothness of the cursor trajectory is a goal of this research, but the more important aim is to reduce target acquisition time, thereby increasing the bandwidth or communication efficiency of the user. Visual examination of the recorded results showed that a typical trial consisted of a reaching movement, directed roughly from starting point to target icon, followed by a "settling" phase in which the cursor was already more or less at the target, but the subject was struggling to keep it within the circle. Therefore, to generate an intended or ideal movement for training purposes, a two-stage approach is used. During the initial reaching phase of each trial, at each instant, the intended velocity is taken to be along the line from the instantaneous location to the target. A bell-shaped profile of intended velocity is assumed, since this is the way normal reaching movements are generated [13]. Then, during the final settling phase, the intended movement is assumed to be a motionless cursor held at the center of the target circle. Thus, for most trials, the training scenario provides a target acquisition time considerably shorter than the raw data.

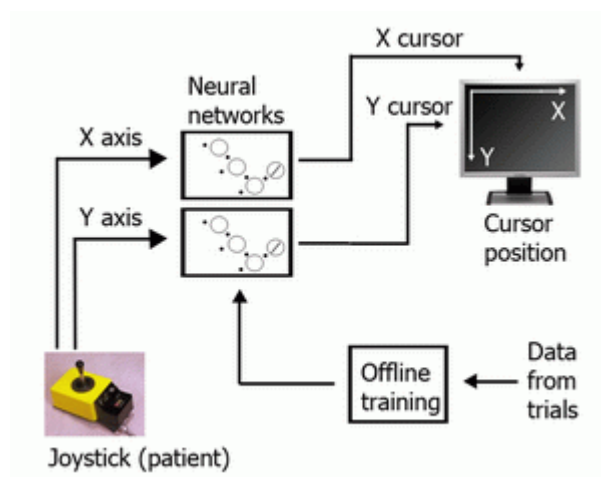

Fig. 3. Description of the complete system. The patient moves the joystick to move the cursor. We get information from both X and Y axis. This information will be the input of the networks, being their outputs, the modified and current cursor position.

III. Results

The first subject exhibited mild athetosis, while the other two were more severe. Fig. 4 presents the results of a typical trial from the second subject. The solid line shows a straight line from start to target. The dotted line shows the raw trajectory recorded from the subject. The performance of all subjects is summarized in Table I. The elapsed time is the total time for the trial, including the 2 s of dwell time within the target circle. Transition time indicates the time from the start of the test to the first crossing of a line, perpendicular to the ideal trajectory, which passes through the center of the circle. This is taken as a rough approximation of the time of transition from the gross reaching movement to the settling phase. Thus the time required for settling on the target once the cursor is in the vicinity of the target can be taken roughly as the difference between the elapsed and transition times. The deviation in pixels is the average of the perpendicular distance from the cursor to the straight ideal trajectory at each instant.

TABLE I
RAW PERFORMANCE OF SUBJECTS IN RECORDED TRIALS

	Subj. 1 mean (σ)	Subj. 2 mean (σ)	Subj. 3 mean (σ)	Overall average mean (σ)
Elapsed time (s)	13.2 (4.9)	8.5 (4.0)	6.5 (2.2)	9.4 (5.2)
Transition time (s)	7.5 (3.3)	3.6 (2.1)	2.7 (1.4)	4.6 (3.5)
Deviation (pixels)	65 (30)	78 (49)	80 (44)	75 (43)

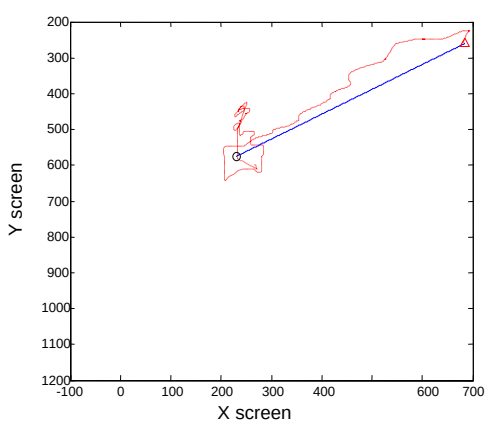

Fig. 4. Results from a typical trial. The solid line shows a straight path from start to target. The dotted line shows the raw trajectory recorded from the subject.

IV. Discussion

The planned filtering approach is presently being tested in simulation, using both the raw athetoid data presented here, and a model of athetosis based on [2]. Subsequently, the technique will be tested online with the same human subjects as before. It is hoped that this technique will offer a statistically significant reduction in target acquisition time for persons with athetosis when using a graphical user interface.

Acknowledgment

We thank the subjects who participated in the trials.

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