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Algorithms for Target Prediction for Computer Users with Athetosis

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***Abstract*—Athetosis is a movement disorder that afflicts numerous persons with cerebral palsy, resulting in significant problems in their control of computer interfaces. As a step toward increasing the efficiency of icon selection by computer users with athetosis, we have implemented three techniques to reduce the time of target acquisition: transition assistance via directional gain variation based on target prediction during initial movement toward the target, settling assistance via gain reduction when in the vicinity of a predicted target, and expansion of the predicted target as the cursor approaches it. The paper describes each method, and presents results from evaluation of each method using a closed-loop model of a human subject with athetosis, trained using recorded data, at three different severity levels.**

I. Introduction

ATHETOSIS is a movement disorder exhibited in certain cases of cerebral palsy. In addition to introducing a involuntary stochastic component of motion, it also reduces the bandwidth of purposeful movement [1]. The resulting derangement of voluntary movement is often considerable [2]. Given the ubiquity of personal computers in the modern workplace, the problems experienced by persons with athetosis in computer use are a major concern from an occupational therapy standpoint [3].

Because computer users with athetosis have difficulty avoiding extraneous gross motion with a standard computer mouse, an isometric or force-sensing joystick was used in this research [4]. In previous experiments involving a common icon-clicking task, subjects with athetosis often succeeded in clicking the intended icon, but were slow to reach it [5]. Therefore the goal of this research is to increase efficiency in computer use for such persons by predicting the intended icon and thereby reduce the time needed to acquire it.

For purposes of the development of assistive strategies, the time required to acquire a target icon was divided conceptually into two parts: transition time (or rise time) and settling time (Fig. 1). We define transition time as the time from the start until the first crossing of an imaginary line through the center of the target, perpendicular to the line connecting the starting point and the target. Settling time is then the time from the end of transition until the "click" or selection of the target. Because control of a mouse button for clicking is often prohibitively difficult for users with athetosis, dwell time of 2 s inside an icon was used to indicate selection of the icon; this made the settling time especially important.

This paper describes the implementation of a variety of assistive techniques for icon acquisition by users with athetosis. As a prelude to testing the techniques with human subjects, this paper presents the results of testing each technique with closed-loop models of athetosis, developed previously using data recorded from three human subjects during icon-clicking tasks [6].

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II. Methods

A. Prediction of Most Probable Target

The assistance techniques described herein are intended to assist the user in acquiring the intended target icon. Prediction of the most probably intended target is therefore an essential first step in the process. The most probable target icon is estimated using the prediction technique of Murata [7]. The prediction method is based on the time history of the cursor movement vector. The cursor movement is defined by an endpoint and a starting point that correspond with the position of the cursor in the current sampling interval and the previous sampling interval. The angle θ_{ij} between the instantaneous movement vector and the instantaneous vector toward the center of a given icon is computed for each icon j on the screen at each time i. The target icon with the smallest integral (or running sum) of angle values is predicted to be the intended target.

B. Variable-Gain Filter

In operation, the cursor position on the screen is updated as follows:

$$\begin{bmatrix} c_x \\ c_y \end{bmatrix}_{i+1} = g \cdot \begin{bmatrix} \frac{1}{2048}\left(f_x - 2048\right) \\ \frac{1}{2048}\left(f_y - 2048\right) \end{bmatrix}_i + \begin{bmatrix} c_x \\ c_y \end{bmatrix}_i$$

where c_x and c_y are the coordinates of the screen cursor, and f_x and f_y are the unconverted joystick force readings (with 11-bit resolution) in the two coordinate directions. The value g is a variable gain that is used to assist the user in minimizing time to target during the transition and settling phases, as described in the subsequent sections.

C. Transition Assistance

In order to speed the cursor toward the predicted target, with the goal of reducing transition time, a variable gain was implemented as a function of θ_i, the direction toward the predicted target icon at time i.

$$g_t = 1 + (g_{max} - 1)e^{-\left(\frac{\theta_i^2}{\sigma_t^2}\right)} \quad (1)$$

so that the cursor update is then

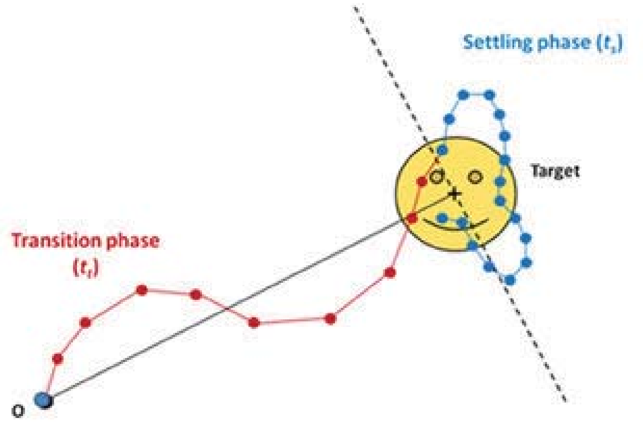

Fig. 1. Definition of transition and settling phases for the purposes of this study. Transition (in red, on the left) begins at the start of the trial and ends at the first crossing of the imaginary line passing through the target and perpendicular to the line between the target and the start point. The settling phase begins at the end of transition and ends at the time of icon selection, as indicated by a dwell time of 2 s inside the icon.

$$\begin{bmatrix} c_x \\ c_y \end{bmatrix}_{i+1} = g_t(\theta_i) \cdot \begin{bmatrix} \frac{1}{2048}\left(f_x - 2048\right) \\ \frac{1}{2048}\left(f_y - 2048\right) \end{bmatrix}_i + \begin{bmatrix} c_x \\ c_y \end{bmatrix}_i \qquad (2)$$

where g_{max} was empirically selected to be 1.5, 1.75, and 2.0 for mild, moderate, and severe athetosis, respectively (Fig. 2). The selected values of σ_t were $\pi/6$ for mild and moderate athetosis, and $\pi/12$ for severe athetosis. Figure 2 shows the resulting directional gain for the three severity levels.

D. Settling Assistance

To reduce settling time, reduced control-display gain is used. This is similar to prior work in "sticky icons" [8, 9], except that in this case the region of reduced gain extended beyond the icon, rather than being reduced only inside the icon (Fig. 3). The reduced gain was implemented by augmenting the previous equation (2) with a settling gain,

$$g_s(d_i) = 1 - \left(1 - g_{\min} e^{-\left(\frac{d_i^2}{\sigma_s^2}\right)}\right)$$

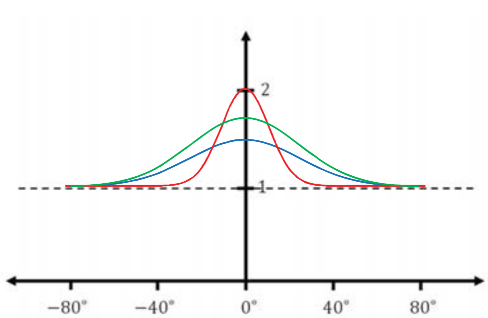

Fig. 2. Directionally-variable gain, g_t, used in (2) for transition assistance. The values for mild athetosis are shown in blue, moderate athetosis in green, and severe athetosis in red.

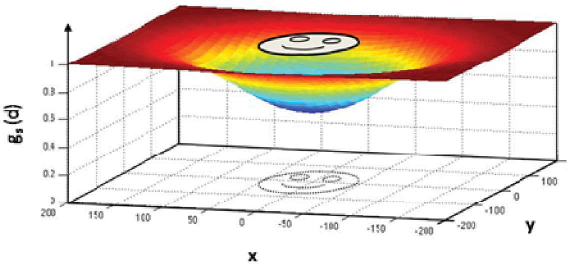

Fig. 3. Settling assistance: variable gain, g_s, imposed in the vicinity of the predicted target icon.

where d_i is the distance at time i from the cursor to the most probable target, so that the cursor update (2) becomes

$$\begin{bmatrix} c_x \\ c_y \end{bmatrix}_{i+1} = g_s(d_i) g_t(\theta_i) \cdot \begin{bmatrix} \frac{1}{2048}\left(f_x - 2048\right) \\ \frac{1}{2048}\left(f_y - 2048\right) \end{bmatrix}_i + \begin{bmatrix} c_x \\ c_y \end{bmatrix}_i .$$

The empirically selected values used for testing were g_{min} = 0.3 and σ_t = 70 pixels.

E. Variable Target Size

Fitts's law is a model of human targeting movement that describes the time required to move from an initial position to a target, as a function of the distance to the target and the size of the target [10]. It has been frequently applied to studies of computer interfaces [11]. One form of Fitts's law for a two-dimensional pointing is

$$T = a + b \log_2\left(\sqrt{\left(\frac{D}{W}\right)^2 + \eta\left(\frac{D}{H}\right)^2} + 1\right)$$

where T is the average time to complete the movement, D is the distance from the starting point to the center of the target, W is the width of the target along x, H is the height of the target along y, and a, b, and η are empirical constants that characterize each subject [12]. Given this equation, it is reasonable to expect enlarging of the predicted target to decrease acquisition time [13]. We have incorporated linear enlargement of the predicted target within a fixed radius of the predicted target. The way in which the size of the predicted icon increases from its normal diameter, Q_0, is determined by the distance between icons (D_{obj}), and by the selected parameter values:

- C_Q, specifying how much to increase the target size; and
- C_D, specifying the distance at which the size begins to increase.

The increase in target size (Fig. 4) is governed as shown in Fig. 5. The values $C_Q = 2$ and $C_D = 0.5$ were used for testing.

F. Athetosis Model

To enable simulation of algorithm performance with a human in the loop, a quantitative model of athetosis was used [6]. Models of three persons with athetosis were created using

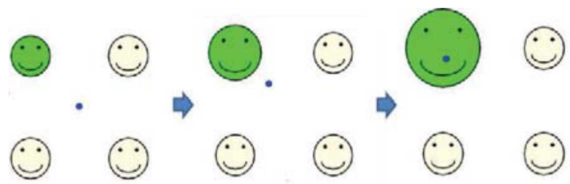

Fig. 4. Size of predicted target icon increases as cursor approaches it, in order to decrease acquisition time.

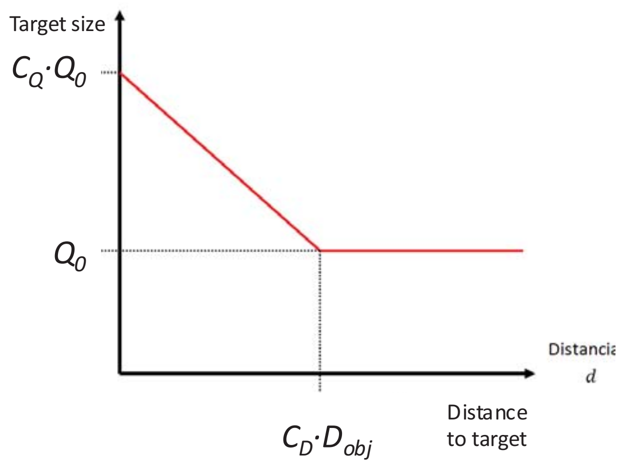

Fig. 5. Variable target size used to decrease acquisition time.

recorded data from a set of 100 icon-clicking trials performed by each subject. The state vector for the model is:

$$\mathbf{z}[i] = \begin{bmatrix} c_x[i] \\ c_y[i] \\ \dot{c}_x[i] \\ \dot{c}_y[i] \end{bmatrix}, \qquad (3)$$

where the states are the position and velocity of the cursor in x and y, relative to the target location. The model maps $\mathbf{z}[i]$ to $\mathbf{z}[i+1]$. Matrices of state column vector inputs and outputs, taken sample by sample over the entire set of N=100 trials, can be constructed as follows:

$$\mathbf{IN} = [\mathbf{z}[1] \quad \ldots \quad \mathbf{z}[N-1]] \qquad (4)$$

$$\mathbf{OUT} = [\mathbf{z}[2] \quad \ldots \quad \mathbf{z}[N]]. \qquad (5)$$

The matrix, **M**, computed using the pseudoinverse of **IN**, as follows,

$$\mathbf{M} = \mathbf{OUT} \cdot \mathbf{IN}^{+} \qquad (6)$$

provides a minimum norm least squares solution to the mapping of the inputs in **IN** to the outputs in **OUT**.
The model is

$$\mathbf{z}[i+1] = \mathbf{M} \cdot \mathbf{z}[i] + a \cdot (\|\mathbf{z}[i]\| + b) \cdot \mathbf{f}[i+1] \qquad (7)$$

where **f** is a colored noise, included in order to model the known stochastic component in athetosis [1], and a and b are constants tuned individually for each subject so that the time to target (click) and the click success rate of the model matched those of the real subjects. Further details on the model are provided in [6].

G. Evaluation in Simulation

The evaluation in simulation involved the completion of target acquisition trials using the closed-loop athetosis model described above. Nine circular target icons were used, each with a diameter (Q_0) of 100 pixels, in a circular pattern with a radius of 280 pixels. A time limit of 15 s per trial was imposed; any trial that exceeded this limit was recorded as a failure. Each task began with the cursor at the center of the circular pattern. Clicking was indicated by 2 s of cursor dwell time within a target icon.

Three different degrees of severity were used in the test: mild, moderate, and severe athetosis, as produced by three different patient-specific models, trained using data from three individual patients diagnosed with these three levels of athetosis.

There were four test conditions:
1) Unaided;
2) Transition assistance;
3) Settling assistance;
4) Variable target size.

A total of 18,000 tasks were simulated: 1500 tasks under each test condition at each of the three severities. Data from each test condition were analyzed in order to quantify the success rate, the transition time (mean and standard deviation), and settling time (mean and standard deviation). Two-tailed Student t tests were used to assess statistical significance of results.

III. Results

A. Mild Athetosis

Because of the mildness of the athetosis in this model, the success rate in each test condition was 100%. The variable target size test condition reduced settling time by 35%. The settling assistance reduced settling time by 31%. Transition assistance reduced the transition time by 38%. Transition assistance did not significantly change the settling time, and settling assistance did not significantly change the transition time; apart from the above exceptions, transition and settling times were significantly reduced in each case. Total acquisition time was significantly reduced by each of the three types of assistance.

TABLE I
Simulation Results for Mild Athetosis

Test condition	Success Rate (%)	Total time (s)	Transition time (s)	Settling time (s)
Unaided	100	4.9±1.3	2.3±0.8	2.6±1.2
Transition assistance	100	4.1±1.3	1.4±0.8	2.7±1.2
Settling assistance	100	4.1±1.0	2.3±0.8	1.8±0.6
Variable target size	100	3.9±0.8	2.2±0.8	1.7±0.6

There were 1000 trials for each test condition. Results for time indicate mean ± standard deviation.

B. *Moderate Athetosis*

Results for simulated moderate athetosis are shown in Table II. The transition assistance reduced the transition time by 32%, but actually decreased the success rate slightly; it did not significantly change the settling time. Settling assistance reduced the settling time by 25%, and increased the success rate to almost 100%, although it significantly increased transition time also. However, the variable target size is seen to be the most helpful, reducing settling time by 52%, and again increasing the success rate to almost 100%, albeit without significantly changing the transition time. The remaining differences between means were significant. Total acquisition time was significantly reduced by each type of assistance.

TABLE II
SIMULATION RESULTS FOR MODERATE ATHETOSIS

Test condition	Success Rate (%)	Total time (s)	Transition time (s)	Settling time (s)
Unaided	93.9	7.3±4.0	3.3±1.5	4.0±2.5
Transition assistance	90.0	6.5±2.8	2.3±1.3	4.2±2.7
Settling assistance	99.5	6.5±2.3	3.5±1.6	3.0±1.8
Variable target size	99.7	5.2±1.8	3.4±1.5	1.8±1.2

There were 1000 trials for each test condition. Results for time indicate mean ± standard deviation.

C. *Severe Athetosis*

For the model of severe athetosis, transition time was high. Over 10% of the trials failed due to running over the time limit of 15 s. The trajectories generated by the model have a strong random component.

The transition assistance provided modest benefits, reducing the transition time by 15%, and slightly increasing the success rate. Transition assistance did not significantly change the settling time. Settling assistance produced no significant change in total acquisition time; it significantly reduced settling time (by 14%), but significantly increased transition time. Again, the variable target size provided the greatest benefit, reducing settling time by half, increasing the success rate to 98.4%, and reducing total acquisition time, despite having no significant effect on transition time.

TABLE III
SIMULATION RESULTS FOR SEVERE ATHETOSIS

Test condition	Success Rate (%)	Total time (s)	Transition time (s)	Settling time (s)
Unaided	89.9	8.6±2.6	5.8±2.3	2.7±1.6
Transition assistance	92.4	7.7±2.6	4.9±2.3	2.8±1.8
Settling assistance	94.9	8.4±2.6	6.1±2.5	2.3±1.1
Variable target size	98.4	7.1±2.3	5.8±2.4	1.3±0.8

There were 1000 trials for each test condition. Results for time indicate mean ± standard deviation.

IV. DISCUSSION

The simulation results obtained suggest the general feasibility of the types of targeting assistance implemented, and provide at least a reasonable expectation that testing with human subjects will provide a significant benefit. For each of the three severity levels tested, most types of assistance offered a significant reduction in total acquisition time. The one exception was setting assistance in the case of severe athetosis, which did not significantly change the total acquisition time, because the significant reduction in settling time was offset by a significant degradation in transition time.

The next step in this work is to test the presented techniques with human users, to obtain a definitive validation of the benefits provided. The fact that, in the simulations presented here, settling assistance significantly degraded transition time in the case of both the moderate and severe athetosis, indicates that ultimately it would be advantageous if a suitable method could be developed to avoid the settling assistance at first, and perhaps phase it in gradually at a later point in each trial, although the question of when best to do so is problematic, of course, given that the intended target is unknown.

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