Abstract

This paper describes the framework for a branch of augmented cognition research performed at the Adaptive Multimodal Laboratory at the University of Hawai‘i and a specific application involving the identification of a computer user based on the forces applied to a computer mouse (i.e., click signature) during a task. Data was collected from six people during a pilot study. Two methods used to identify users were a back propagation neural network and discriminant analysis. Results indicate that the discriminant analysis was slightly better at identifying users than the neural network, but it’s primary advantage was that it required less data preparation. Continuous identification of the user is possible with either method. Successful identification of the user is a useful first step to proceed to the next stage of the research framework, which is to identify the user’s cognitive state for implementation in an augmented cognition system.

1. Introduction

This paper is divided into two parts. The first section describes the framework of the augmented cognition research performed at the Adaptive Multimodal Laboratory at the University of Hawai‘i. The second section involves an initial step toward implementation of augmented cognition using the forces applied to a computer mouse. This involves a pilot study where data collected during a task from a force sensitive computer mouse is evaluated using two different methods.

1.1 Framework

The objective of augmented cognition research is to identify user attributes that automatically prompt modifications of information presented to the user to enhance task performance. One of many implementations of augmented cognition would be to automatically identify the level of user attention to a task and to modify the rate of information being presented to optimize task completion. For example, when we read text, we naturally speed through those sections that are not difficult and less relevant to the task at hand, while slowing down at sections where comprehension of the information is critical to the task.

Unless all the information needed for a task is presented on a visual display at once, this natural visual scanning ability must be combined with a method to present the missing information. Presentation of information at a fixed rate is the least desirable since information necessary to a task may be missed because the rate of presentation is too rapid to be understood. Also, presenting information too slow for the user creates an excessive load on the user’s memory when a large number of items must be remembered for a long period of time [1]. A better method of information presentation would be at the control of the user, but this method would require constant rate adjustments which would interfere with optimum performance. The best method would be for the information to be presented at a rate optimal for the task at hand without the user constantly being taken away from the task to make information presentation rate adjustments. To make the best option possible, the choice of user attribute which would control the rate of information presentation must be passively acquired so as to not impact on task...
performance. The assessment method must continuously identify those attributes of the user that can direct the automatic change of the rate of information presentation. This best method would be an example of augmented cognition.

Figure 1 shows a Venn diagram of attributes common to all people and attributes specific to the individual. The attributes of interest are those which can be obtained passively without interfering with the task performance of the individual. As the diagram shows, there is an expected overlap between all people and the individual. Figure 2 shows the attributes of three different people. Note that although each person has some common attributes, each person also has a slightly different set of distinguishing attributes. When multiple measurements are taken, either from a single sensor, multiple sensors or multiple sensors measuring different attributes, as shown in Figure 3, it becomes possible to distinguish these people from each other. Figure 4 shows that an individual can also have attributes that vary depending on their cognitive state (e.g., alert, stressed, etc.). The individual cognitive state can then be used to augment cognition. In the example of the previous paragraph regarding the pace of information presentation, detection of stress or reduced alertness could be used to direct the computer to reduce the speed of information presentation.

The problem of distinguishing between people (i.e., Figure 3) and an individual’s cognitive states (i.e., Figure 4) appear to be very similar, but there are significant differences. The set of attributes that easy differentiate people can be completely different from the set of attributes that will indicate a person’s different cognitive state. Also, given any specific passively observable attribute, differences between people are likely to be easier to detect than the different cognitive states of an individual. Yet, differentiating between people and a person’s different cognitive states follow the same methodology.

1.2 Pilot Study

The characteristics of the desired attribute to measure would be that it be passive, continuous, allow the identification of user’s cognitive state and identify the unique characteristics of the user. The passive types of
measure that have been used are: eye position tracking (i.e., gaze) [2], pupil dilation [3], galvanic skin conductivity, heart rate and peripheral body temperature [4]. The attribute measured in this paper is force applied to computer mouse button while clicking responses to a task (See Figure 5). When a user performs a task requiring a computer mouse, the force applied to the mouse button is constantly measured. The authors noticed that each person appeared to have a unique pattern. Also, there is precedence for using pressure or force measurements on a tool as an indication of a person’s cognitive state since increased pressure while writing has been associated with increased stress [5].

The objective of a pilot study was to evaluate two potential methods of using the forces applied to the computer mouse button (i.e., click signature) during a task to identify a user. Two methods of identification are compared: back propagation neural network and discriminant analysis.

2. Method
2.1 Subjects

Six university graduate student and faculty participated in this pilot study.
2.2 Apparatus

A computer mouse modified to measure the force applied to the buttons was used in conjunction with a custom designed data acquisition board which transmitted the data to the computer. This mouse from all outward appearance looked exactly like a standard computer mouse. All data was recorded by the computer the user was performing the task on.

2.3 Task Description

Seven sets of tasks were presented. The task was to click each square as it appears. There are seven sets of tasks with 16 squares to each set. The position of the squares displayed are shown in Figure 6.

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Figure 6. Position of squares displayed.

1. Set 1 presents the square targets in sequentially order. This task was that fastest and easiest for the subject.
2. Set 2 presents the square targets in a pseudo-random sequence. The pseudo-random sequence was constructed to eliminate sequences of two or three adjacent squares being presented and required the subject to move the computer mouse approximately the same total distance as the subsequent pseudo-random sequences of subsequent sets. This sequence increased the amount of attention required to perform the task which increases the task completion time.
3. Set 3 presents small square targets in a pseudo-random sequence. Psuedo-randomization and smaller square targets increase the required attention and difficulty.
4. Set 4 presents low contrast square targets in a pseudo-random sequence. This method is a different way to increases the attention and difficulty of the task.
5. Set 5 presents small low contrast square targets in a pseudo-random sequence. This method compounds all previous methods of increasing the attention required and the difficulty.
6. Set 6 presents the square targets in a regular sequence of three square targets (i.e., second square left 2, third square right 1). This set is used for as part of another experiment looking for implicit learning.
7. Set 7 presents the square targets as in set 2, but presented in a different pseudo-random order. The seventh set is used as a comparison standard to Set 2 to determine the change in performance over the experiment.

Figure 7 shows the image presented to the subject. There is a single square which the subject must click before proceeding to click the next square.

2.4 Procedure

Subjects were instructed to click the start button, then boxes as they appeared on the screen. The subjects were warned that boxes may become more difficult, but to do their best.

2.5 Data Analysis

Data from the experiment was analyzed using two different methods to identify the subjects from their mouse click signatures. The first method of identification used a neural network with back-propagation training (see Figure 8) and the second method used a discriminant analysis of the mouse click signatures. For the neural network, the over 100 mouse clicks from each subject was broken into two mutually exclusive sets. The first set, called the training set, used the first 90 mouse clicks signatures of each subject to create a mean click signature for each of the six subjects (see Figure 2). Mean click signature of subjects were used since previous experiments using the actual data produced a neural network with poor results. The second set, called the testing set, consisted of the last ten mouse clicks of each subject.
The Neuroshell program, by Ward Systems Group was used for the analysis. The neural network parameters were adjusted and the network was trained using the mean click signatures of the subjects, then identification of the test set mouse clicks was performed. The data from the test set was used to determine the percent of correct identifications to subjects. Several runs were performed to determine the best way to present the data to the network and the optimum number of hidden layer nodes (i.e., five nodes).

A discriminant analysis, using SPSS software by SPSS Inc., was performed using the first 100 mouse click signatures of the subjects. Using discriminant analysis, a cross validation identification of the subjects from mouse click signatures were performed. Cross validation uses discriminant analysis functions which excluded the data of the mouse click signature being identified.

3. Results

The neural network was able identify the subject from a single mouse click signature an average of 68% of the time. Using the discriminant analysis method, identification of the subject from a single mouse click signature was an average of 79% of the time (see Figure 9).

For the neural network method of identification, on average, three mouse clicks would be required to have an accuracy greater than 95%. For the discriminant analysis method of identification, on average, two mouse clicks would be required to have an accuracy greater than 95%.

4. Discussion

The neural network required several experiments to determine the optimum number of hidden nodes that would produce the optimal identification output. The discriminant analysis produces five functions used to identify the subjects and was slightly better at identifying subjects. The discriminant analysis method was less complex to implement. The discriminant analysis two-dimensional plot indicates that some subjects are very similar to each other while others are very different (see Figure 10), but when multiple dimensions are incorporated, discrimination is possible. A study of a large population of subjects is necessary, but the discriminant analysis method seems to be the simpler method of analysis.

There are several methods that can be implemented to improve the reliability of user identification. First, a
higher sampling rate of the force on the mouse will provide more information to differentiate subjects. Second, the use of multiple mouse clicks. Third, a combination of the force applied to a computer mouse with individual characteristic response latencies. Finally, a combination of the mouse click signature with other biometric information.

In this pilot study, the mouse click signature is shown be able to indicate the identity of the subject. There is precedence for using pressure or force on a tool as an indication of a person’s cognitive state. Increased pressure while writing has been associated with increased stress [5], so forces applied to a computer mouse could be used as an indicator of stress. A procedure similar that used to identify subjects can be used to identify an individual’s different cognitive states. The methodology to determine user identification, demonstrated in this pilot study, is the initial step toward using forces on a computer mouse to identify the cognitive states of the user and subsequently implementing different modes of augmented cognition.

5. References


6. Acknowledgments
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