An Adaptive Word Prediction Interface

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1 Statement of the Problem

Word prediction is a technique often used by individuals with disabilities as a means of increasing the rate with which they can enter text into a computer by reducing the number of keystrokes entered per word. A word prediction system typically operates by presenting a list of "best guesses" for the word the user is currently entering. As the user continues to enter letters, the system updates the list of word predictions to conform to the user's input. When the word the user is entering is displayed on the list, the user can select the word with one keystroke (often, one of the number keys on the keyboard), and the system will then complete the word for the user. Table 1 lists the parameters defining the word prediction interface that can have an effect on a user's text entry rate.

Koester and Levine [9] demonstrated that while word prediction often reduces the number of keystrokes required to enter text, it does not necessarily follow that it will also reduce *the time* required to enter that text. The success of word prediction as a text entry rate enhancement technique depends on a variety of factors including the settings of the system parameters described in Table 1, the strategy employed by the user, and the success that the word prediction system has in predicting what words the user is entering. Koester and Levine [10] developed several models that accurately predicted text entry rate enhancement based on these factors, which we are using as the basis for an adaptive word prediction system that automatically modifies its parameters to maximize a user's text entry rate.

2 The Need for Adaptive Assistive Technology

Optimizing the fit between technology and the user is critical for realizing the potential benefits of assistive technology[1]. Ideally, the clinician who recommends an assistive technology, the client who uses the technology, and the assistive technology itself should share the responsibility for making certain that the client's needs are matched as closely as possible.

Often it is the clinician, such as a speech/language pathologist, rehabilitation engineer, or occupational therapist who assumes primary responsibility for configuring the system to best take advantage of the user's abilities. For example, when configuring an augmentative communication system for an individual, a clinician evaluates a client's motor, perceptual, and cognitive skills and sets values for that client's access method based on this evaluation. These settings may be modified by the client, family members, or attendants, but in practice this happens only occasionally.

It is, of course, appropriate that clinicians play a central role in configuring assistive technology. Clinicians are trained to evaluate clients and to translate those evaluations into effective assistive technology interventions, and a periodic review of a person's abilities is crucial to identify the best fit between that individual and his or her associated assistive technology. However, intermittent intervention from a clinician, if it occurs at all, is best suited to deal with changes in a person's needs and abilities that occur slowly and represent relatively permanent states (e.g., due to practice or a change in medical condition). Changes that occur more rapidly and are transient in nature (e.g., due to fatigue or periodic spasticity) require a more rapid and flexible response. For example, the settings for a user's computer access system may be changed by a clinician every few months in response to increased skill on the part of the user, but it is unreasonable to expect a clinician to be standing at the ready to constantly adjust the system's parameters as the client's energy level cycles throughout the day.

It is often possible for the client to reconfigure an assistive technology on their own in response to their changing needs. While this may work for some people, for others it may impose unacceptable performance costs, especially when adaptation must happen quickly in response to changing task requirements [18]. In these instances the assistive technology itself is in the best po-

[1]The term *assistive technology* refers to a broad range of technologies (wheelchairs, augmentative communication devices, alternative computer access hardware and software, etc.) designed to assist individuals with disabilities.

Table 1: Word Prediction Interface Parameters.

Parameter	Explanation
Show	The number of keystrokes that must be entered before word prediction list is displayed.
Hide	The number of keystrokes that can be entered (once the word prediction list is displayed) before the list is removed.
Llen	The number of words displayed in the word prediction list.
MWS	The minimum number of letters in each word within word prediction list.

sition to manage system adaptation. Currently, however, assistive technologies make little or no effort to assist the clinician or client in this task. Few systems record performance data and even fewer aid the clinician in interpreting and acting upon this data in terms of system modifications. There are currently no commercially available assistive technology systems that actually modify aspects of their interface based on measurements of user performance.

3 Related Research

While no commercially available assistive technology products provide adaptive interfaces, several research projects have explored the use of adaptive interfaces to improve the ability of assistive technologies to meet the needs of users [1, 13, 14]. The work described in this paper was preceded by efforts to develop an adaptive interface for one-switch row-column scanning [15].

One-switch row-column scanning is a very slow method of communication. An able-bodied individual using an optimally-designed matrix of 26 letters and a space can produce between 6 and 8 words/minute using this method [4, 8]. Despite its limitations, row-column scanning fills an important niche within technology access methods by providing an affordable alternative for individuals with limited movement and vocal abilities. Hence, despite increasing interest in speech recognition, eye-tracking, and direct-brain interfaces for accessing assistive technology, there remain valid reasons for seeking to enhance performance using row-column scanning.

One method for increasing text entry rate with row-column scanning is to dynamically change the configuration of the matrix of items (letters, punctuation marks, words, etc.) to reduce the number of scan steps required to reach the most likely selections. Another alternative is the use of a rate-enhancement technique such as word prediction or abbreviation expansion. However, recent work indicates that the increased cognitive load these methods impose on the user may result in little to no improvement in text generation rate [5, 7].

A third alternative, which we are presently investigating, is the possibility of increasing a user's text entry rate by dynamically adapting the parameters controlling a system's scanning behavior during run-time. Table 2 lists the possible parameters that could be modified in an adaptive row-column scanning system. Our goal is to develop a method for matching these parameters to each individual user. If a given scan delay (row scan delay, column scan delay, initial row scan delay, initial column scan delay) is not long enough, the user's text entry rate is likely to decrease due to increased errors. A scan delay that is too long, on the other hand, will have few errors but will also fail to produce the maximum possible text entry rate.

The primary advantage of our approach is that it attempts to increase text entry rate without complicating the visual display. This implies that dynamically adapting the scan delay should impose less additional cognitive load upon the user than other rate enhancement techniques. Another advantage of this approach is that an adaptive system would be responsive to both permanent (e.g., due to learning) and transient (e.g., due to fatigue) changes in the user's ability.

Cronk and Schubert [3] represents an early attempt to automate the selection of row-column scanning parameters. An expert system was developed that, given a set of user characteristics, would usually make the same scan delay adjustments as a panel of three speech/language pathologists. The system was tested with six subjects, five of whom reported general agreement with the actions of the system. Unfortunately, no results were reported regarding the effect of the expert system's actions on user performance.

4 Modeling Approach

In the word prediction application, our modeling approach is based on previous work [10] in user performance modeling with word prediction using the Keystroke-Level Model [2]. The key factors represented in the model are the characteristics of the user, the strategy used to search the word list, and the configuration of the word prediction system. Two model parameters represent the user characteristics: t_s for the time it takes the user to search the word list and t_k for the time required for the user to press a key. Two other parameters represent the task presented by the system: S for the number of searches required per character,

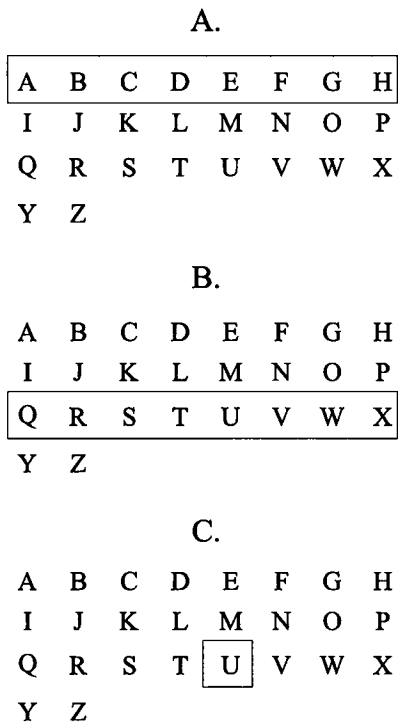

Figure 1: Three switch-hit row-column scanning. In panel A, the system is row-scanning and the first row is highlighted. In panel B, the target row has been reached and the switch has been pressed for the first time. In panel C, the system is scanning through each column within the target row. The switch is pressed a second time when the target letter (U) is reached.

Table 2: Row-Column Scanning Parameters.

Parameter	Explanation
Initial Row Scan Delay	Additional delay before the system begins scanning through rows
Initial Column Scan Delay	Additional delay before the system begins scanning through the columns within a row
Row Scan Delay	The amount of time a given row remains highlighted, the amount of time the user has to select the currently highlighted row
Column Scan Delay	The amount of time a given column remains highlighted, the amount of time the user has to select the currently highlighted column
Column Scans	The number of times the columns within a row are scanned if no selection is made once a row has been selected

and k_{sav} for the proportion of keypresses saved by use of word prediction. The user parameters are independent of each other, and the two system parameters are jointly determined by the system configuration (e.g., how many words are in the list) and the user's search strategy (e.g., when he/she chooses to search the list).

The model equation for the text generation rate with word prediction is derived as follows. The average time necessary to generate each character is modeled as the sum of two components: the number of list searches per character multiplied by the search time and the number of keypresses per character multiplied by the keypress time during word prediction use. This is expressed in equation form as:

$$T_{wp} = (S)(t_s) + (1 - k_{sav})(t_k)$$

where T_{wp} is expressed in seconds per character. The text generation rate (measured in characters per minute) is then simply:

$$60/T_{wp}$$

This model is useful to the development of an adaptive interface for word prediction in two ways. On a qualitative level, the model illustrates which factors influence user performance with word prediction and the relative strength of these factors. This conceptual understanding influences design choices regarding which factors should be monitored by the adaptation mechanism and those factors which may by most fruitful for the adaptation mechanism to adjust. Quantitatively, continuous model simulations of user performance are an integral part of the adaptation mechanism. Quantitative model simulations will help the adaptation mechanism address the key question "How is user performance likely to change in response to a change in a given parameter?"

5 Formulation of a Computable Task

We are currently evaluating two separate approaches to using our user model within an adaptive word prediction user interface. The first approach uses a probabilistic reasoning technique known as *Bayesian Networks* [12] to make decisions that conform with the conclusions of the model. The second approach uses the model itself as the evaluation function for a *Genetic Algorithm* [6]. Both approaches are described in brief below.

5.1 Bayesian Network Approach

This approach builds on previous research performed by the investigators in developing adaptive computer access [15] and wheelchair [17] interfaces. This approach uses Bayesian networks to combine information about the task and the user's performance in order to make adaptation decisions. Bayesian networks provide a method of modeling a situation in which causality is important but our knowledge of what is actually going on is incomplete or uncertain by allowing us to describe things probabilistically [12]. Bayesian networks can be thought of (albeit somewhat simplistically) as a means of organizing information to allow the convenient application of a form of Bayes' theorem:

$$\Pr(H \mid e) = \frac{\Pr(e \mid H)\Pr(H)}{\Pr(e)}$$

In our application, H represents the adaptation decisions that are possible in the current situation, e is the set of observations, and the value of the probability $P(H \mid e)$ represents the probability that a particular adaptation decision is the correct decision given the available evidence.

5.2 Genetic Algorithm Approach

This approach will use the Genetic Algorithm to identify the best set of parameters for an individual. The Genetic Agorithm is a model of machine learning which derives its behavior from a metaphor of some of the mechanisms of evolution in nature. This is done by the creation within a machine of a population of chromosomes, in essence a set of character strings that are analogous to the chromosomes that we see in our own DNA. The individuals in the population then go through a process of simulated "evolution". In practice, the genetic algorithm is implemented by having arrays of bits or characters to represent the chromosomes. Simple bit manipulation operations allow the implementation of crossover (combining two chromosomes), mutation (altering one or more bits within a single chromosome), and other operations.

In the word prediction application, each genetic string in the population will be composed of four substrings, with each substring corresponding to a different parameter (see Table 1). The estimates of user performance provided by the user model will be used as the evaluation function, which is used to determine the relative fitness of each string within the population. Strings with higher fitness values are more likely to survive and produce offspring through the crossover operation.

6 Method of Obtaining Feedback

The parameters that will be used to make adaptation decisions can be divided into *task parameters* and *user*

parameters. Task parameters of interest include measures of dictionary coverage of the text being typed, word prediction accuracy, average length of words entered, and average keystroke savings (k_{sav}). User parameters of interest are average keypress time (t_k) and average list search time (t_s).

Task parameters are distinguished from user parameters in that most task parameters (with the exception of the average number of searches per character, S) can be calculated exactly from dictionary contents, word prediction performance, and the text entered by the user. User parameters, on the other hand, must be estimated by the software from observations of the user's typing behavior. Average keypress time will be estimated based on the average time between keystrokes when there are no words in the word prediction list. Average list search time will be estimated based on the time for the user to perform successful searches from word prediction lists of varying lengths.

7 Project Status

We have implemented a testbed for recording subjects' actions while entering text with (and without) a word prediction system active. Several able-bodied and disabled subjects have completed trials in which they entered text under a variety of interface configurations [11, 16]. In trials involving subjects with disabilities, system configuration had a meaningful effect on text entry rate for half of the subjects, with an average of over 60% difference between configurations. For the other half of the subject group, the effect of configuration was less clear, perhaps confounded with the effects of individual variation and increase in skill level over time.

At this time, the Bayesian network that will be used to make adaptation decisions is under development. Key issues include what observations are related to each interface parameter that can be modified and whether one Bayesian network should be used to make decisions for all interface parameters or whether each interface parameter should be modified by a different Bayesian network. We are also examining key issues involving the implementation of the Genetic Algorithm, particularly the exact representation that will be used for parameters within the genetic string, and how crossover will be implemented.

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