PERSONALIZED ADAPTIVE PDA INTERFACE[1]

Siska Fitrianie
Leon J.M. Rothkrantz

Man-Machine-Interaction Group, Delft University of Technology
Mekelweg 4 2628CD Delft,
The Netherlands,
E-mail: {s.fitrianie, l.j.m.rothkrantz}@ewi.tudelft.nl

KEYWORDS
Adaptive (Graphical User) Interface, human-computer interaction, text prediction, text entry for PDA.

ABSTRACT

User demands for usability in mobile context due to the small size of personal data assistants (PDAs) challenge traditional input design. An on-screen keyboard that offers an easier and faster method of entering text with a pen on PDAs, has been developed. We have developed a method for adapting its predictive ability according to user's personal word usage, input context and syntax rules. Frequently used characters are presented to the users in different key sizes and color contrasts according to their relative probabilities to aid visual searching. For this purpose, an experiment has been conducted on which and how to use (user's) data source for faster prediction. In this experiment, we compared four dictionaries recorded from the British National Corpus, personal documents, chat logs and personal e-mails. The experimental results show ways to improve the performance of the word prediction and the language coverage of the word completion.

INTRODUCTION

The needs of being able to access information anytime and anywhere makes personal digital assistants (PDAs) more popular due to its portability and facility for wireless connection. The PDAs are now designed to be smaller and sleeker. They are advancing to a more powerful device and equipped with increasing numbers of features. Word processors, personal schedulers, e-mailing, language programming and other traditional desktop applications are increasingly available on this platform. However, PDA's text input is still a bottle-neck (Karlson et al. 2006).

Mobile activity situations often require multitasking. The requirements include unstable environment, eyes-free interaction, competition for attention resources and varying hand availability (Pascoe et al. 2000). In demanding situations, e.g. walking and talking, where the user's attention cannot be devoted fully on inputting, improvement in the input method performance is highly desired. Recent research has been done in developing speech recognition for text entry. However, speech recognition is not yet used for general purpose text input on mobile devices (MacKenzie and Soukoreff 2002). The reason is because the current technology still makes speech input less suitable for mobility (Bousquet-Vernhettes et al. 2003). Therefore, manual pen-based text entry remains one of the dominant forms of user interaction on PDAs. These devices accommodate single-handed interaction to offer users freeing a hand for holding the device or other mobile activity demands.

One of the challenges of a new keyboard design is the user requirement on ability to use it without the need for extensive practice (Bohan 1999). Handwriting is arguably the most intuitive input interaction method for PDAs. However, current handwriting recognition technology is still around 87%-93% accuracy (MacKenzie and Chang 1999). Lalomia (1994) reported that users are willing to accept a recognition error rate of only 3%. Although it can be improved to 97% after 3 hr of practice (Santos 1992), human's hand text entry speed is limited to 15 wpm (Card et al. 1983). Thus, the entry rates of handwriting can never reach those of touch typing - 20-40 wpm (MacKenzie and Soukereff 2002).

In contrast to physical keyboards, with on-screen touch keyboards the key layout has a major effect on the text entry performance (Isokoski 2004). This is because typing is strictly sequential. To type a character, we have to move the pen from one key to the next and during this time there can be no preparation for the following key. Thus, minimizing the distance to be traveled can greatly enhance text entry speed. Nevertheless, visual scan time is still necessary to distinguish an individual character from the group (Eriksen and Eriksen 1974). Familiarity with the location of the characters on the keyboard does appear to facilitate entry performance (MacKenzie et al. 1999). Entry performance can also be increased by adding visual cues to draw a user's attention to the next most probable character(s) in a word they are typing (Magnien et al. 2004). In such situation, certain characters should have a distinctive appearance that differs from others (Wolfe 1994). One of the ways is by expanding some keys' size that allows users to select larger target to improve target acquisition time (McGuffin and Balakrishnan 2002).

[1] The research reported here is part of the Interactive Collaborative Information Systems (ICIS) project, supported by the Dutch Ministry of Economic Affairs, grant nr: BSIK03024

Everyone has his/her own style of writing and communication, especially in personal writing, such as mail, SMS, personal note or diary. The style reflects on word choices and compositions in a sentence. An adaptive text entry system is able to provide prediction to a user based on its experience with this user and improve its ability based on the user's needs over time. The system collects traces of user linguistics compositions, constructs knowledge about the user from these traces through learning, and using this knowledge to alter its future interactions. In this way, the resulting text entry system is personalized to the individual user.

In this paper, we introduce the idea of an adaptive and personalized single-handed pen-based text entry on a PDA. We develop an n-gram based predictive feature that is able to propose next-character and next-word selections based on the user's personal way of formulating language, the context of the user's task and the English syntax. Using the results of this prediction, the user interface is able to display characters in different sizes and color contrasts according to their relative probabilities.

The structure of this paper is as follows. In the following section, we start with related work. We continue with describing our experiment in developing our system's dictionary. Further, our text prediction is presented. Then, our developed pen-based text entry model is described. Finally, we conclude the paper.

RELATED WORK

In practice the most popular pen-based keyboard design is still the QWERTY layout and its language-specific adaptations. It has been observed that this layout is not optimal for pen-based text entry because the distance between common adjacent characters is too far. Previous work in developing adapted keyboard layouts for handhelds and single-handed use has concentrated on alternative key configuration for improving entry speed, such as Metropolis (Zhai et al. 2000), ABC (MacKenzie et al. 1999), and OPTI (MacKenzie and Zhang 1999). Fitaly keyboard introduces two space bars and the characters arrangement so that common pairs of characters are often on neighboring keys (Langendorf 1988). An extensive study on pen-based text entry has been reported in (MacKenzie and Soukoreff 2002).

Typically, tapping-based text entry, in which the pen must be tapped for selecting characters, requires intense visual attention, virtually at every key tap, which prevents the user from focusing attention on text output (Zhai and Kristensson 2003). Gesture-based text entry methods interpret informal pen motions as character inputs, such as T-Cube (Venolia and Neiberg 1994) and Quikwriting (Perlin 1998). Another example is Cirrin (Mankoff and Abowd 1998), which arranges the characters inside the perimeter of an annulus (Figure 1). This circular layout means that when the user places his/her pen in the center of the Cirrin, the distance to each character is equal. The most commonly used digrams are nearest to each other, therefore distances traveled from character to character are usually shorter than a QWERTY-based on-screen keyboard. However, since there is not any "head-up" feature, a user must attend to the interface when entering text. A space is entered by lifting the pen. Punctuation and mode shifts are accomplished by using an auxiliary technique, such as keys operated by the nondominant hand.

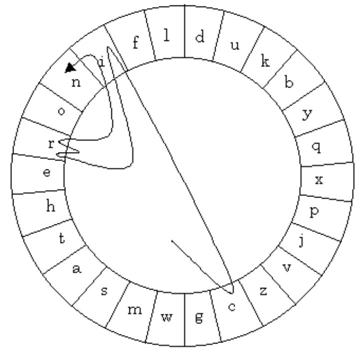

Figure 1: Standard Cirrin (Mankoff and Abouwd 1998)

Unexpected results appearead in a research of real-time expanding Cirrin's key size as the pen approach it (Figure 2 - Cechanowicz et al. 2006). It indicates a slower and more error prone user performance than the standard Cirrin. The problem is in finding an optimum threshold between two adjacent keys, so that the user does not make incorrect selection. Another reason is the position of "backspace" key being outside the Cirrin wheel, which is needed for faster error recovery.

Figure 2: Expanding Cirrin (Cechanowicz et al. 2006)

SHARK is a hybrid method on the ATOMIC keyboard that augments tapping-based input with gesture-based input (Zhai and Kristensson 2003). The researchers reported that visually guided tapping is easier for novice users. Since simple tapping movement may feel tedious to repeat for prolonged use, gesture-based input is preferred by experts.

Some text input techniques have been developed with both movements minimizing and predictive features. T9 text entry works by comparing sequences of key presses to a stored database of possible words (Tegic Communication). Dasher uses prediction by partial matching, in which a set of previous symbols in the uncompressed symbol stream is used to predict the next symbol in the stream (Ward et al. 2000). It employs continuous input by dynamically arranging characters in multiple columns positioning the next most likely character near the user's pen input. The options are presented to the user in boxes sized according to their relative probabilities, to optimize the movement time.

Because the character arrangement constantly changes, Dasher demands user's visual attention to dynamically react to the changing layout.

EXPERIMENT

An important aspect of our proposed text entry system is the word prediction, which is based on the user's personal way of writing. But, which source can be used so that our system can learn and trace the user's writing style? How useful are these sources for faster prediction? How to use this data source? To answer these questions, an experiment has been performed by comparing common English words use and personal use.

To collect data for analysis, we have prepared a set of words from four different sources: (1) most common English words from British National Corpus (BNC), (2) 5.5 Mb personal documents, such as words documents, spreadsheets, and schedulers, (3) 4.2 Mb personal chat logs (ZetaTalk 2001-2003) and (4) 7.2 Mb corporate e-mails (Corrada-Emmanuel). The author of the personal documents is a researcher in the field of multimodal communication. The chat logs contain a multitude discussion from philosophical topics like life aftertime or aliens presence to the science and government acknowledgement on aliens. The e-mails were taken from internal e-mails of the Enron corporation, an energy company in Houston, Texas.

As the first step, we collected all words from each dataset and counted their frequency. The BNC database has provided word frequency counts. We selected 5500 most frequent words from each personal dataset. These words appear at least 20 times in each dataset.

Which and How Useful are the Data Sources?

In this step, we compared the coverage of the common English words represented by BNC Database to all personal datasets. Table 1 shows that the BNC Database can cover in average 87% for each context and about 74% for the union of all personal datasets. Most words that are not covered by the BNC database from personal documents are abbreviations, names and specific terms, such as: "xml", "website", "lexicalized" and "synset" in the field of computer science. 78% of the words in e-mail datasets that are not covered by the BNC database are addresses and names of persons, products and organizations. Other 11% are specific terms, such as "teleconference", "worldnet" and "unsubscribe" in the field of communication network. Some of the words in chat logs that are not covered by the BNC database are popular terms in chatting or informal conversation, such as "lol" (laugh out loud), "okidok" or "yup" (OK), "thingie" (such thing), "heck" (hell) and emoticons, for example: ":)" for smile and ":))" for laughing. Others (91%) are names and internet addresses.

Table 1: The Coverage of BNC Database towards the Personal Datasets

Unigram	Number of words	BNC Database (166261 words)	A∨B∨C
A:Personal Docs	5500	4982 (90%)	49%
B:E-mails	5500	4740 (86%)	49%
C:Chat Logs	5500	4754 (86%)	49%
A∧B∧C	1685	1674 (99%)	15%
A∨B∨C	11168	9579 (85%)	

As a next step, we calculated the bigram frequency for each dataset and discarded those bigrams that contain words not covered by the BNC database. Table 2 shows that the BNC database has the lowest coverage for the personal document dataset. Although all words in each bigram are covered by the database, the compositions of them may not. Most of these bigrams are terminologies in a specific domain. For example: "human interaction", "usability testing", and "interface design" in the field human-computer interaction; "multimodal fission", "dialogue management" and "natural language" in the field multimodal system; and "emotion expressions", "facial recognition", and "muscle coordination" in the field nonverbal communication. They are considered as the most frequent bigrams (at least 29 times).

Most bigrams in the e-mail dataset that are not covered by the BNC database are terminologies in corporate domain, such as: "financially bankrupt", "employee transition", "expense report" and "retirement plans". Small amount bigrams are in the field of communication, such as "intended recipient", "conference call", and "video connection". The chat logs also contain bigrams in a specific domain that are not covered by the BNC database, such as: "planet x", "pole shift", and "star children". Small amount bigrams are about science, such as "gravity particle", "volcanic ash" and "orbital path".

Table 2: The Coverage of BNC Database towards the Personal Datasets

Bigram	Number of bigrams	BNC Database (726000 bigrams)	A∨B∨C
A:Personal Docs	54829	33994 (62%)	56%
B:E-mails	10505	7016 (83%)	11%
C:Chat Logs	36801	29809 (81%)	37%
A∧B∧C	2426	2348 (96%)	2.4%
A∨B∨C	89275	68742 (77%)	

Moreover, although the coverage of the BNC database to the convergence of the personal datasets is quite high (99% for unigrams and 96% for bigrams), these datasets themselves share a small amount of the corpus (15% words and 2.4% bigrams). One of the reasons could be that these datasets are not retrieved from the same source (nor produced by the same person). Another reason could be that each dataset is taken from a specific context. Thus, these findings show that there is a strong correlation between user personal word usage and the context of the user task.

How to Use the Data Sources?

In this step, we built a hierarchical hash-table for each dataset. This hash-table simulates user character entries to serve as a prefix before a completion of a word without any prediction (see an example in Figure 3). The end of a hierarchy shows that there is no longer possible word for the next prefix input. The different columns show that some character inputs are necessary for completing the word, for example for the word "thereby" a user needs to input "t", "h", "e", "r", "e", and "b" to distinguish this word with "there".

Prefix(es):

h	e	s/r/o	e/m/r	b/e/o	m/i

Hash-table:

to					
	the				
	their				
		thesaurus			
		these			
		thesis			
		there			
				Thereby	
		thermo			
					thermometer
		theory			
				Theoretic	
					theorist
	then				

Figure 3: A Part of a Hierarchical Hash-table for The First Character "t" (Schematic View – Read From Left to Right)

Using hash-tables, we analyzed how many appropriate number of character entries are necessary before a user can select a completion. Figure 4 shows the coverage of each dataset. According to the graph, a user has in average a 3.6% chance of being able to enter the word she/he desires in just one character entry. It also shows an almost similar coverage of 5500 most frequent words in all datasets for every prefix.

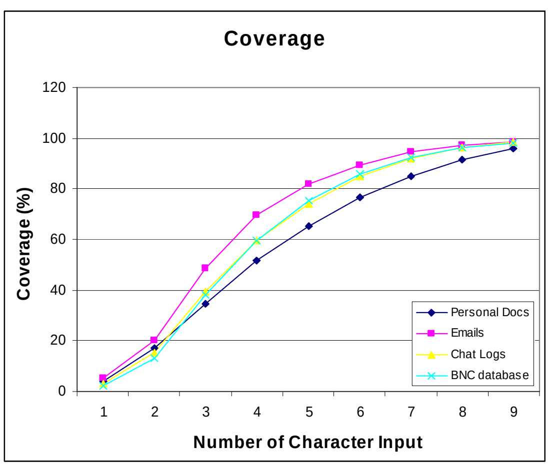

Figure 4: Coverage of 5500 Most Frequent Words from Four Datasets

Assume the completion is using all words in datasets: (1) BNC database contains 166261 words, (2) personal document dataset contains 19121words, (3) chat log dataset contains 15432 words and (4) e-mail dataset contains 13046 words.
It proves that the performance of the completion is degraded due to the inclusion of lower frequency words (Figure 5).

The completion will be more effective using a relatively small dictionary containing the highest frequency words in the English language based on normal word usage. This implies to the previous finding, which shows that the personal datasets share only a small number of the corpus. A set of context-based dictionaries (for each user's context) would be more efficient for the completion than one large dictionary that contains all possible corpora.

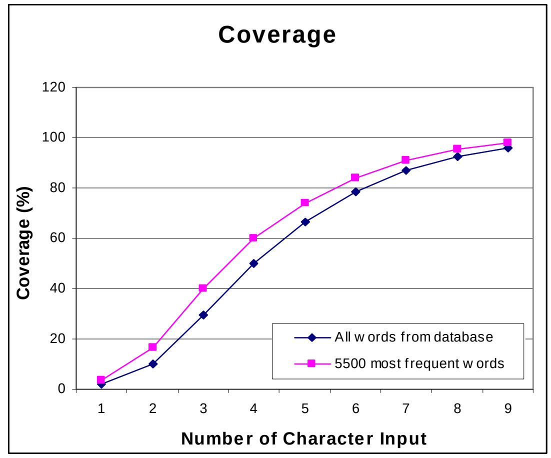

Figure 5: Average Coverage of All Words Versus 5500 Most Frequent Words from Four Datasets

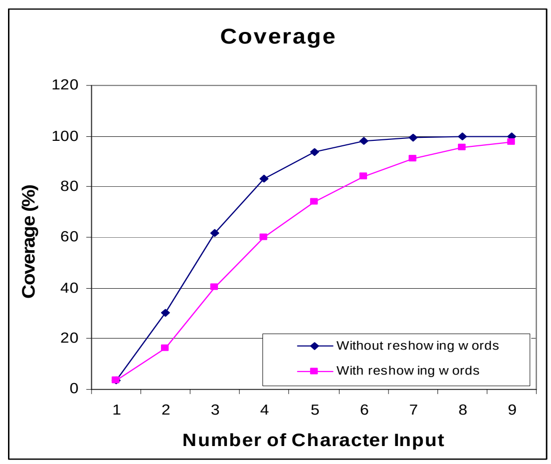

Figure 6: Average Coverage of the 5500 Most Frequent Words from Four Datasets with Reshowing Words and without Reshowing Words

Figure 6 shows if the completion is not reshowing the same word completions once these words have been shown for a given word being entered. For example, when "ther" is written, "there" is one possible completion. If "e" is inputted next, a better option is to show a different word completion, for example "thereby". By this way, those empty cells, for example from "there" to "thereby" and from "thermo" to "thermometer", are disappeared. This option will reduce the number of inputs to select a desired word, since users sometimes miss the initial appearance of the word they intended and enter more characters than necessary. This finding is coherence with Wobbrock and Myers (2006).

COMPUTATION OF CONDITIONAL PROBABILITIES

Our developed text entry system has a *word prediction*, which consists of several components (see Figure 7). The prediction result is then presented to the user. Each component in the developed word prediction is explained below.

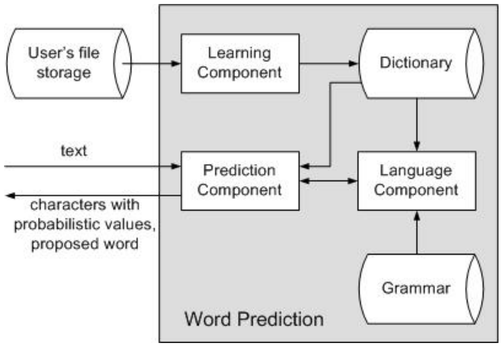

Figure 7: Schematic View of Our Developed Word Prediction

Dictionary

Our word prediction system has two main dictionaries, such as: (1) a common dictionary and (2) a user-personal dictionary, which consists of sub-dictionaries for every user's context. The current implementation defines three contexts, such as: (a) writing a document, (b) writing an e-mail and (c) chatting. Both dictionaries consist of a unigram list, a trigram list and a bigram list. They include information about part-of-speech tags and frequencies of each element. The common dictionary has been extracted from the BNC database. It provides the same frequency for all users at the beginning. The user-personal dictionary is empty at the beginning. During interaction, the system will change and adapt both dictionaries.

Learning Component

When the text entry system is used at the first time, the *learning component* parses all personal documents in the user's storage. The user may specify folders and files that can be extracted by this component. Otherwise, by default, it will extract first all personal word processor documents (including spreadsheets and schedulers) and e-mails (including its address book). This process fills the personal dictionary and updates the common dictionary.

The learning component updates the dictionaries by two ways. Firstly, it extracts the user's inputs during interaction. Finally, this component extracts the dictionary from the user's storage frequently. The user may schedule this process.

Prediction Component

The *prediction component* operates by generating three lists of suggestions for possible words after the first character is inputted, such as: (a) from the common dictionary, (b) from the personal dictionary and (c) based on the context of user's task. If the input is the character of the first word in a sentence, this component will return all words that start with the same set of characters.

After the first word is inputted, the next possible words are predicted using a statistical approach that was derived from a probabilistic language model. The probability of a sentence is estimated with the use of Bayes rule as the product of conditional probabilities:

$$P(s) = P(w_1, w_2, ..., w_n) = \prod_{i=1}^{n} P(w_i \mid h_i) \qquad (1)$$

where h_i is the relevant history when predicting a word w_i. To predict the most likely word, a global estimation of the sentence probability is derived which is computed by estimating the probability of each word given its local context (history). Our prediction component uses estimating conditional probabilities of trigrams type features. The probabilities obtained from uni-, bi- and trigrams are weighted together using standard linear interpolation formula. The system will calculate the prediction on all three dictionaries.

The results of the prediction are ranked based on their probability. The information about the part of speech tag given a word in both suggestion lists is also included, since a word form may be ambiguous and adhere to more that one part-of-speech. These lists are filtered to have all words that start with the same set of characters as the user's input.

Language Component

Besides for improving the input speed by personalizing the word prediction, our developed text entry system aims to improve the quality of syntax. Most available word-predictions have been developed based on n-gram frequencies, which often suggest syntactically implausible or excluding more-plausible but lower probability from its suggestion list. This can confuse users by inappropriate suggestions. Therefore, the overall motivation for the *language component* is to enhance the accuracy of the prediction suggestions. This component does not by itself generate any prediction suggestions but filter the suggestions produced by the n-gram model so that the grammatically correct word forms will be presented to the user prior to any ungrammatical ones.

Input to this component is three ranked lists of the most probable word forms according to the n-gram model with their part-of-speech. The language component checks all suggestion words based on its tense and morphology rule. The current implementation is able to check and change the form of a verb (tense), a noun (pluralism) and an adverb using WordNet (Fellbaum 1998) in three steps: (1) stemming all words, (2) creating all forms for each word, and (3) checking in the WordNet whether each new form is a correct form. Since a word form may be ambiguous and adhere to more forms, all word forms are added to the suggestion lists with the same probability.

The language component parses the sentence fragment entered so far. The part-of-speech tag model requires information about the possible part-of-speech tags of each word in the user's sentence. For this purpose, we used the QTAG POS Tagger (Tufis and Mason 1998), which is a (n-grams) probabilistic tagger using a dictionary of (tagged) words and a matrix of tag sequences with corresponding probabilities. The output of this tagger is the part-of-speech of each word (for example noun, verb, and adjective) in a sentence. Our developed language component assigns a value to each word in the suggestion lists whether it is confirmed by grammatical, ungrammatical or out of scope of the grammar. Based on those values, the ungrammatical suggestions are discarded from the lists. Future work needs to be done to update the POS tagger, therefore, it includes the user-personal corpora into its dictionary.

Since only one suggestion will be presented to the user, this component will choose the highest probability word from the context-based dictionary preceded the personal and common dictionary. The suggestion from personal dictionary will be chosen preceded the common dictionary, if the context-based suggestion list is empty or the probability is lower than a threshold. Future research still needs to be done in defining optimum threshold of a suggestion's probability value.

PEN-BASED TEXT ENTRY MODEL

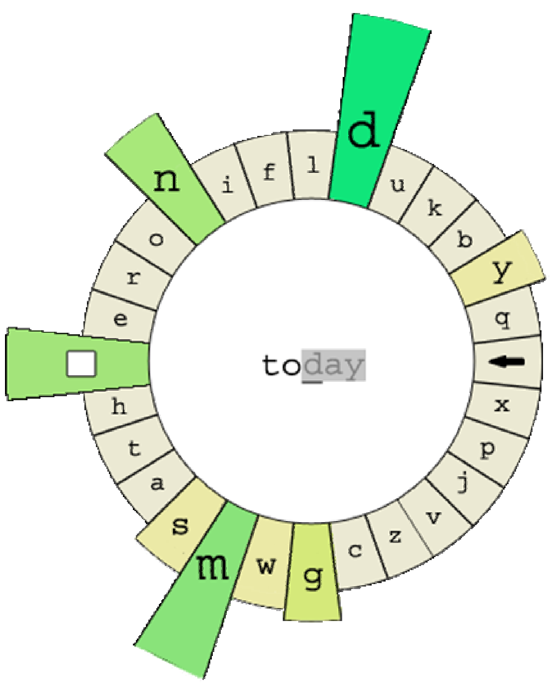

Figure 8: Personalized Adaptive Cirrin. The Previous Input Contains "go shopping"

Figure 8 shows our developed pen-based text entry on a PDA. The interface gives visual cues, such as different key sizes and color contrasts, for the next-character and next-word selections, without changing the character layout. A standard on-screen keyboard does not fit with this specification, but on a keyboard whose characters are arranged on the circumference of a polygon or a circle or in two parallel columns, it is possible to expand the keys' size. Therefore, we adopt the Cirrin device's (Mankoff and Abowd 1998) method to display all characters in a circular way. Our design differs from the original Cirrin in four aspects: (1) geometry, (2) character set, (3) input style and (4) word completion.

Geometry

Similar to the original Cirrin, we use a single column circular layout, which creates a ring of characters. The middle of the ring is an input area, where selected characters of a single word are displayed. The current implementation of our text entry system has a flowing text area, where a user can compose a message. To support direct perception of the user, every time a character is selected on the input area, it will be displayed in the text area too.

The visual cue on a key gives information about the likelihood of the next character selection. The current implementation uses 200% expansion and the most contrast color for the most likelihood characters. The key of lower probability characters is expanded and colored based on its proportion to the highest probability character.

Character Set

We use the original Cirrin's character set (26 English characters) and layout, which was based on a scoring function to calculate the most used adjacent characters. The difference is two additional characters: space and backspace. Although, like punctuation and return, they can still be entered using any common character-level input technique, these common characters are added into the ring to support a quick error recovery (Cechanowicz et al. 2006). In the event of an erroneous completion, the user can make a backspace stroke or press the backspace key, undoing the selection and restoring the completion as it appeared before. This makes completions quickly undoable. An additional matrix 6 x 5 is placed on the right side of the circle for numbers, shift, return, control, period, punctuations and comma.

Input Style

Unlike the original Cirrin, which allows only a gesture-based input, our developed text entry system allows both tapping-based and gesture-based input and combination of them. The transition of both inputs works as follows. When entering a word, the user may begin with the tapping mode and continue with the gesture mode. By this way, the new selections will be appended to the previous selections. In the gesture mode, when the user stops dragging and lifts the pen from the screen, a space will be added at the end of the input word. The user may continue inputting the next characters for the next word. When a space is selected after a word, this word will be flushed to the text area. Selecting a backspace on a space will result the word back in the input area.

Word Completion

As the user enters each keystroke, our developed text entry system displays the most likely completions of the partially typed word on the input area. It indicates which characters of the word are not yet selected. As the user continues to enter characters, the system updates the suggestion accordingly. The special feature of our word completion is that it only shows a suggestion word completion once after this suggestion is turned down by selecting the next character. If the intended word is displayed, the user simply can select it with a single tap on the input area. The system will flush this word to the text area and add a space next to the new word.

CONCLUSION

Learning from previous research on developing pen-based text entry for PDAs, we have developed a personalized and adaptive text entry system. Our developed on-screen keyboard offers a fast input and allows users to input less tedious, less visually demanding and fast error recovery by four ways: (1) visual cue for next-character prediction, (2) next word completion, (3) combining both tapping-based input and gesture-based input and (4) adding space and backspace into the circle. Inspired by Cirrin (Mankoff and Abowd 1998), the characters are arranged in a circular ring. In this research, we aim at exploring a method for adapting the text entry system according to user's personal word usage the context of user's task to reduce the time necessary to search for a desired key.

An experiment has been performed by comparing the most common English words taken from the BNC database with personal datasets, such as personal documents, e-mails and chat logs. Although the BNC database covers most of the personal corpus, the experimental results showed that the intersection of the personal datasets is small. Moreover, the word completion showed better performance using a relatively small dictionary containing the highest frequency words based on normal word usage. This indicates that, besides personal word usage, the ability to improve effective text entry and typing rate may also dependent on the context of the user task. The current implementation of our developed text entry system has a personal dictionary that consists of user context-based sub-dictionaries.

Besides saving time and energy in inputting the number of characters for completing a desired word, the proposed text entry system can also assist the users in the composition of well-formed text. For this purpose, our developed word prediction uses both syntactical and n-grams probabilistic approaches to predict next possible words. In displaying the prediction result, the system takes an assumption that a suggested word is rejected after the user selects the next character. By this way, the user can have a better language coverage since each suggestion word is shown only once.

The primary results show that the developed personalized adaptive approach offers a usable text entry device to investigate. To understand all issues involved and the full potential this our text entry system, especially in mobile situation and how people experience this, requires a great deal more research and intensive evaluations in the future. Currently, we improve the developed system by providing supports for better user-system interactions.

REFERENCES

Bohan M., Phipps C.A., Chaparro A. and Halcomb C. 1999. A Psychophysical Comparison of Two Stylus-Driven Soft Keyboards. *Proc. of Graphics Interface*, 92-97.

Bousquet-Vernhettes C., Privat R. and Vigouroux N. 2003. Error Handling in Spoken Dialogue Systems: Toward Corrective Dialogue, *Proc. of ISCA*, USA.

British National Corpus, Unigrams and Bigrams, Retrieved on January 5, 2007, from http://natcorp.ox.ac.uk

Card S. K., Moran T. P. and Newell A. 1983. *The Psychology of Human–Computer Interaction*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Cechanowicz J., Dawson S., Victor M. and Subramanian S. 2006. Stylus Based Text Input Using Expanding CIRRIN. *Proc. of AVI*. ACM Press, New York, NY, 163-166.

Corrada-Emmanuel A. (n.d.). *Enron E-mail Dataset Research*. Retrieved in January 5, 2007, from http://ciir.cs.umass.edu/~corrada/enron/

Eriksen B.A. and Eriksen C.W. 1974. Effects of Noise Letters Upon the Identification of a Target Letter in a Non-Search Task. *Perception and Psychophysics*, 16, 143-149.

Fellbaum C. 1998. *WordNet: An Electronic Lexical Database*. The MIT Press.

Isokoski P. 2004. *Manual Text Entry: Experiments, Models, and Systems* (Ph.D. thesis), Report A-2004-3, Department of Computer Sciences, University of Tampere, Finland. http://www.cs.uta.fi/~poika/vk/isokoski_thesis_complete.pdf

Karlson A., Bederson B. and Contreras-Vidal J. 2006. Understanding Single Handed Use of Handheld Devices. Lumsden Jo (Ed.), *Handbook of Research on User Interface Design and Evaluation for Mobile Technology*, in press.

LaLomia M.J. 1994. User Acceptance of Handwritten Recognition Accuracy. *Proc. of ACM CHI*, Boston, MA, USA, 2:107.

Langendorf D.J. 1988. Textware Solution's Fitaly Keyboard V1.0 Easing the Burden of Keyboard Input. *WinCELair Review*.

MacKenzie I.S. and Chang L. 1999. A Performance Comparison of Two Handwriting Recognizers. *Interacting with Computers*, 11(3), 283 - 297.

MacKenzie I.S. and Soukoreff R.W. 2002. Text Entry for Mobile Computing: Models and Methods, Theory and Practice. *Human-Computer Interaction*, 17: 147-198.

MacKenzie I.S. and Zhang, S.X. 1999. The Design and Evaluation of a High-Performance Soft Keyboard. *Proc. of ACM CHI*, 25-31. New York: ACM.

MacKenzie I.S., Zhang S.X. and Soukoreff R.W. 1999. Text Entry using Soft Keyboards. *Behaviour and Information Technology*, 18, 235-244.

Magnien L., Bouraoui J.L. and Vigouroux N. 2004. Mobile Text Input with Soft Keyboards: Optimization by Means of Visual Clues, *Proc. of Mobile HCI*, Springer-Verlag , 337-341.

Mankoff J. and Abowd G. D. 1998. Cirrin: A Word-Level Unistroke Keyboard for Pen Input. ACM UIST'98, 213-214.

McGuffin M. and Balakrishnan R. 2002. Acquisition of Expanding Targets. *Proc. of ACM CHI*, 57-64.

Pascoe J., Ryan N. and Mores D. 2000. Using While Moving: HCI Issues in Fieldwork Environment. *Transaction on Computer Human Interaction*, 7(3).

Perlin K. 1998 Quikwriting: Continuous Stylus-Based Text Entry. *Proc. of ACM UIST*, 215-216. New York: ACM.

Santos P.J., Baltzer A.J., Badre A.N., Henneman R.L. and Miller M.S. 1992. On Handwriting Recognition System Performance: Some Experimental Results. *Proc. of the Human Factors Society*, CA:Human Factors and Ergonomics Society.

Tegic Communication. 1998. T9. http://www.t9.com/faq.html.

Tufis D. and Mason O. 1998. Tagging Romanian Texts: a Case Study for QTAG, a Language Independent Probabilistic Tagger, *Proc of LREC*, Spain, 589-596.

Venolia D. and Neiberg, F. 1994. T-Cube: A Fast, Self-Disclosing Pen-Based Alphabet. *Proc. of ACM CHI*, 265-270. New York: ACM.

Ward D.A., Blackwell A. and MacKay D. 2000. Dasher – a Data Entry Interface Using Continuous Gesture and Language Models, *Proc. of ACM UIST*, 129-136.

Wolfe J.M. 1994. Guided search 2.0: A revised model of visual search. *Psychonomic Bulletin and Review*, 1(2). 202–238.

Wobbrock J.O., Myers B.A. and Chau D.H. 2006. In-stroke Word Completion. *Proc. of ACM UIST*. Switzerland. New York: ACM Press, 333-336.

Zhai S., Hunter M., and Smith B.A. 2000. The Metropolis Keyboard - An Exploration of Quantitative Techniques for Virtual Keyboard Design. *Proc. of ACM UIST*, 119-128. New York: ACM.

Zhai S. and Kristensson P.-O. 2003. Shorthand Writing on Stylus Keyboard, *Proc. of ACM CHI*, 97-104.

ZetaTalk, Chat Logs – ZetaTalk Live Dec 2001-May 2003, Retrieved in January 5, 2007, from http://ww.zetatalk3.com/index/zetalogs.htm.

BIOGRAPHY

SISKA FITRIANIE was born in Bandung, Indonesia and went to Delft University of Technology, the Netherlands, where she studied Technical Informatics and obtained her master degree in 2002. After doing her two years post-graduate programme at Eindhoven University of Technology, she involves in the Interactive Collaborative Information Systems (ICIS) project, supported by the Dutch Ministry of Economic Affairs, since 2004 as her PhD project at Delft University of Technology. Her project aims at designing and developing models of a computer-human interaction system.
E-mail: s.fitrianie@ewi.tudelft.nl
Webaddress: http://mmi.tudelft.nl/~siska

LEON J.M ROTHKRANTZ received the M.Sc. degree in mathematics from the University of Utrecht, Utrecht, The Netherlands, in 1971, the Ph.D. degree in mathematics from the University of Amsterdam, Amsterdam, The Netherlands, in 1980, and the M.Sc. degree in psychology from the University of Leiden, Leiden, The Netherlands, in 1990. He is currently an Associate Professor with the Man-Machine-Interaction Group, Mediamatics Department, Delft University of Technology, Delft, The Netherlands, since 1992. His current research focuses on a wide range of the related issues, including lip reading, speech recognition and synthesis, facial expression analysis and synthesis, multimodal information fusion, natural dialogue management, and human affective feedback recognition. The long-range goal of his research is the design and development of natural, context-aware, multimodal man–machine interfaces. Drs. Dr. Rothkrantz is a member of the Program Committee for EUROSIS.
E-mail: l.j.m.rothkrantz@ewi.tudelft.nl
Webaddress: http://mmi.tudelft.nl/~leon