Enhancing Access to Situational Vocabulary by Leveraging Geographic Context

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Abstract: Users of augmentative and alternative communication (AAC) aids could benefit from novel methods for accelerating access to contextually relevant vocabulary. This paper describes our initial efforts toward improving access to situational vocabulary through the use of geographic context to predict vocabulary. A corpus of spoken data produced by one able-bodied male speaker across various locations was collected and used to mine location-specific vocabulary clusters. We describe the data mining algorithm and illustrate how context-driven vocabulary organization and prediction can be integrated into an iconic communication system. Correlations between user and algorithm-generated vocabulary patterns highlight discrepancies between actual versus perceived frequency statistics. Thus, device customization may be achieved through a hybrid human-algorithmic approach to vocabulary selection. Endowing the communication aid with knowledge about the user's location-specific vocabulary patterns may help to balance the burden of communication between the system and the user to yield substantial gains in accessing situationally appropriate vocabulary which may in turn accelerate communication rate.

Keywords: Augmentative and alternative communication, Fringe vocabulary, Vocabulary prediction, Situational context

Communication is a slow and effortful process for nearly two million Americans with severe speech impairments who must rely on AAC devices. Communication efficiency is an especially important issue for AAC users who are fluent in the language and thus require access to large vocabularies. Current AAC devices employ a number of techniques to enhance access to frequently used words including message encoding, semantic compaction, and dynamic layouts. All of these methods, however, have practical limits in terms of the number of words that can be retrieved and the cognitive burden imposed on the user. While a significant portion of an AAC user's message consists of core vocabulary items which are common across contexts (Beukelman, Yorkston, Pobleto, & Naranjo, 1984), situational vocabulary (also referred to as fringe or extended vocabulary) may change substantially as the user encounters different topics and settings throughout a day. Although access to situational vocabulary is essential for engaging in timely and relevant conversations, it imposes additional challenges when designing efficient visualization and navigation schemes. Leveraging knowledge about the user's geographic context to guide situational vocabulary prediction has the potential to improve communication efficiency and thereby contribute to optimizing educational, social, and vocational opportunities. This paper reports on an initial exploration aimed at harnessing location-specific vocabulary usage patterns to improve access to less frequently used situational vocabulary.

Background

Communication using AAC devices is significantly slower and effortful compared to typing or speaking (Beukelman & Mirenda, 1998; Goldman-Eisler, 1968; Szeto, Allen, & Littrell, 1993). This mismatch in communication efficiency between AAC users and their able-bodied peers (a) impacts upon the number and type of communication opportunities available (Demasco, 1994; Higginbotham & Wilkins, 1999; Light, Collier, & Parnes, 1985; Müller & Soto, 2002; Simpson, Beukelman, & Sharpe, 2000); (b) contributes to perceptions of cognitive incompetence (Beck, Kingsbury, Neff, & Dennis, 2000; Goodenough-Trepagnier, Galdieri, Rosen, & Baker, 1984; Light 1985, 1988; Hoag, Bedrosian, Johnson, & Molineux, 1994); and (c) limits social and vocational options for AAC users (Beck & Dennis, 1996; Beck, Fritz, Keller, & Dennis, 2000).

In an effort to speed and ease communication most current AAC devices employ some method of enhancing access to frequently used words, including, dynamic layering or thematic organization of vocabulary (Demasco, 1994; Wilson & Fox, 1993), message encoding schemes (Light & Lindsay, 1992), and Semantic Compaction™ (Baker, 1982, 1986). A common metric used for assessing enhanced access to vocabulary items is keystroke savings (see Higginbotham, 1992 for a comparison of keystroke savings across several AAC devices). In other words, measuring the number of physical entries required to construct a message, with and without a given access method. Semantic Compaction™, an encoding scheme in which each icon has multiple meanings, has been shown to improve efficiency by reducing the item set on a visual display (Baker, 1987). Similarly, letter and number encoding schemes in which particular sequences of letters and/or numbers activate words or messages reduce keystrokes (Baker, 1982, 1986; Gardner-Bonneau and Schwartz, 1989; Vanderheiden & Lloyd, 1986). Although encoding schemes may be easier to process and recall, they impose limitations on the size of vocabulary set for reasons of practicality and cognitive load and thus may not be appropriate for fluent users who require access to a large and diverse vocabulary set.

In order to accommodate larger vocabulary sets that cannot be visualized at once, some devices employ dynamic layouts in which single meaning icons are organized into semantically related clusters. To provide the user with a sufficiently rich lexicon, it is essential to have multiple vocabulary pages. There are trade-offs, however, between vocabulary size, the cognitive load of vocabulary management, and the physical load of vocabulary selection.

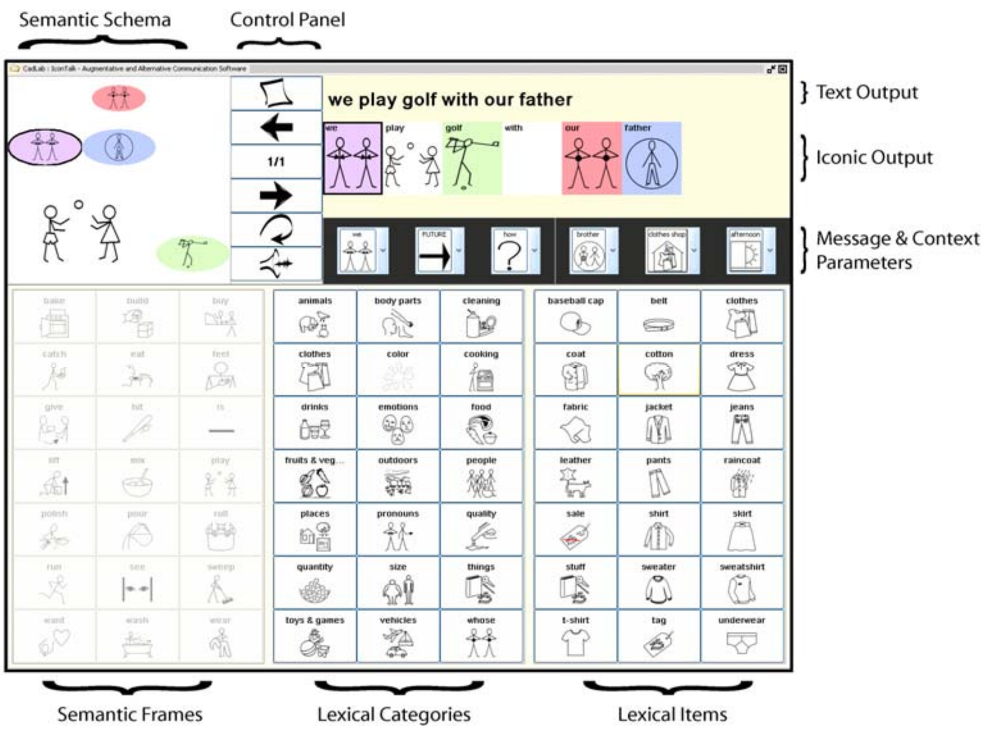
While the above methods can improve access to core vocabulary items, the overall gain is not sufficient to place AAC users on par with their able-bodied peers. AAC users also use words that are not in this core. Beukelman, Yorkston, Pobleto, and Naranjo, (1984) reported a core vocabulary of 500 words based on conversational samples across five non-speaking adults. Across the five participants, only 33% of any given user's communicative utterances could be generated using only those 500 core vocabulary items. One potentially effective strategy for improving vocabulary access for fluent AAC users may be to focus on situationally-dependant words that a user may need in everyday communication. Endowing the communication aid with knowledge about the user's vocabulary patterns in his/her daily routines may balance the burden of communication between the system and the user.

Word prediction is one method of enhancing access situational vocabulary (c.f. Alm, Arnott, & Newell, 1992; Carlberger & Hunnicutt 1998; Copesake, 1997; Foulds, Soede, & van Balkom, 1987; Hunnicut, 1986; Newell, Arnott, Beattie, & Brophy, 1992; Swiffin, Arnott, & Pickering, 1987). Traditional word prediction approaches use statistical information such as frequency and recency of use to order and present a list of the most likely lexical candidates. Although there is almost no learning curve in using word prediction systems compared to encoding schemes, it is not clear whether the keystrokes savings of word prediction translates into improved communication rate or access to the appropriate vocabulary (Higginbotham, 1992; Koester & Levine, 1994, 1997; Lesher, Moulton, & Higginbotham, 1998; Venkatagiri, 1994). The costs incurred by switching between selecting icons or letter and scanning or reading lists of possible items can sometimes outweigh the benefit of reduced keystrokes (Koester & Levine, 1994; Treviranus & Norris, 1987; Venkatagiri).

Especially when the vocabulary size is large, word prediction systems based on a database of word frequencies and inter-word correlations, have a hard time predicting the word that the user actually intended. To address this issue, Lesher and Rinkus (2001) proposed that domain-specific vocabularies may help to constrain the predicted item list. They measured the average keystroke savings of an n-gram prediction model with and without the use of domain-specific vocabularies derived from the Switchboard corpus of telephone transcripts. They demonstrated that endowing the system with domain-specific knowledge can afford keystroke savings between 53-58% relative to models that do not incorporate such information. Constraining the word prediction to offer situationaly-appropriate vocabulary items may decrease the cognitive dissonance associated with searching lists of unrelated and unnecessary words (Renaud, 2002; Venkatagiri, 1994). Since situational vocabulary can potentially be enormous, it requires new ways to thinking about how to make it available to AAC users such that their interactions can be timely and relevant to the topic and setting of conversation.

The idea of using domain-specific vocabulary has made it into some AAC products (e.g., SOLO™ by Don-Johnston, Inc.); however, context is predetermined and vocabulary is predefined by the user or his/her clinician. Balandin and Iacono (1998) showed that even trained professionals have difficulty predicting vocabulary usage. They asked ten professionals (five speech pathologists, three rehabilitation counselors and two teachers) to predict topics and vocabulary of meal break conversations at work. While the professionals accurately predicted some conversational topics, approximately 33% of the key words predicted by the participants did not occur in the conversational sample at all. Thus predicted and actual usage patterns may not always be aligned. Moreover, within a given setting, conversational topics can be diverse. Balandin and Iacono (1998) collected meal break conversational samples from 34 non-disabled participants across four work sites and found that the participants referenced 73 different topics some of which were associated with the day of the week. Upon further analysis of the conversational sample, Balandin, Iacono, and Crews (1999) reported that a small stable core vocabulary of approximately 350 words accounted for 78% of the conversational sample. Fluent AAC communicators may have equally diverse conversations and thus the challenge is to offer the user an appropriate vocabulary set as s/he encounters the various conversation topics, partners, and settings throughout the day. As a first step toward this goal, the present study sought to determine whether vocabulary usage does in fact cluster by geographic location and if so, how effective are these vocabulary clusters for predicting future use in similar contexts? This initial exploration, considers the vocabulary usage patterns of one able-bodied user in various geographically distinct locations. The geographic locations are sensed using a global positioning system (GPS) and the vocabulary usage patterns are mined to extract items that the user may be likely to use in future interactions in those settings.

Figure 1. A screenshot of the iconCHAT interface. © 2007, Rupal Patel. Used with permission.



Our Approach

In this paper we focus on the use of geographic context to accelerate access to situational vocabulary and demonstrate how this may be implemented in an icon-based electronic communication aid. Given that adaptive interfaces which change too often or in unpredictable ways can pose additional challenges, we chose to display the results of the prediction algorithm on our prototype communication system called iconCHAT. This system was chosen for illustration purposes since it provided a test-bed for discussions about the competing trade-offs between vocabulary size and organization and novel visual navigation schemes. For example, given that fringe vocabulary makes up only a fraction (approximately 15%) of the vocabulary used, its was essential that users always had access to core vocabulary items and that only the appropriate fringe vocabulary would be made accessible based on context cues. The general principles discussed, however, are applicable to iconic AAC systems as a whole.

The iconCHAT system is aimed at enhancing communication ease and efficiency by offering a semantically organized method of message construction and a context-driven method of vocabulary organization and prediction (see Figure 1). Vocabulary is organized in three panels: semantic frames, lexical categories, and lexical items. Semantic frames consist of action words or verbs that provide the user with the scaffolding to construct a message [based on case grammars in Fillmore (1968); see also scripts in Schank (1973)]. The frame slots (displayed in the semantic schema), can be filled with lexical items that are classified in their respective lexical categories. Once a message is constructed, the user can generate spoken output using the text-to-speech synthesizer through the control panel. A set of message parameters allow the user to directly control the contents and expression of his/her message. Context parameters inform the user of the system's sensed location, time, and conversational partner [a detailed account of iconCHAT is provided in Patel, Pilato, and Roy (2004)].

We propose using location context to filter and organize vocabulary based on previous usage patterns. Location has been identified as one of the most definitive elements of context in ubiquitous computing (Beigl, Zimmer, & Decker, 2002). It is possible to determine the location of a person with significant accuracy using the GPS in outdoor environments. With the emergence of the E911 directive (Federal Communications Commission, 2005), Assistive-GPS (AGPS) technology will allow location detection in indoor environments in the near future. Endowing an AAC system with location-dependant, user-specific vocabulary may enhance access to situational vocabulary and thereby support timely and appropriate message constructions.

Method

Data Collection

An able-bodied, adult male native English speaker collected a corpus of spoken data over the course of 5 weeks in various geographical locations. Approximately 2.7 hours of audio was recorded on a daily basis for a total of 20.4 hours of silence-removed speech collected over the 5 week period. It is important to note that we began with an able-bodied individual rather than an AAC user in order to collect a sufficiently large corpus of data necessary for building location-dependant vocabulary models. Future plans include gathering location-sensitive expressive output from a group of AAC users.

We captured the location information using the Garmin GPS receiver (Garmin model 35 LVS wearable) and the Geostats GeoLogger (Geostats, Inc. Model DL-04, Version 3.4). The data logger was configured to record latitude, longitude, date and time at five second intervals. Since currently available GPS does not work in indoor spaces, the subject was advised to place the receiver near a window or any such opening with a clear view of the sky.

Spoken utterances were captured on the HP iPAQ h2215 personal digital assistant (PDA) using voice recording software (Resco, sro., 2007). The on-board microphone of the PDA was used with automatic gain control (AGC) disabled to minimize ambient noise. The software was configured to record date and time stamped voice recordings at an encoding rate of 16 bits sampled at 22050 Hz. PDA time and GPS time were synchronized using the U.S. Naval Observatory Master Clock.

The participant was instructed to record conversational speech in his everyday routines. The participant identified certain locations that he felt comfortable recording in and was asked to frequent these locations for several minutes over the course of the week. For reasons of privacy and practicality, not all conversational contexts were sampled. Location clustering revealed eight locations types within his spoken corpus: the campus bookstore, a research lab, various classrooms, clothing stores, electronic stores, grocery stores, the user's kitchen, and his lab meetings.

Subsequent to data collection, each audio file was manually transcribed and coded by location. While we attempted to transcribe the audio files using automatic speech recognition (Nuance Communications, Inc., 2007), we found poor accuracy rates due to the level of ambient noise in the various natural environments. For each of the eight locations, a random sample of 20% of the data was transcribed by two listeners in order to establish inter-rater reliability. Across all locations, the average inter-rater reliability was 98.4%. For words that were not in agreement, an additional pass of the transcription was completed to resolve any discrepancies.

Table 1
Number of Words and Sentences Per Location

Location	*N* of Words	*N* of Sentences
Bookstore	7161	656
Research Lab	5666	474
Classrooms	2962	409
Clothing Store	12256	1122
Electronics Store	8205	687
Grocery Stores	9898	1375
Kitchen	8885	1085
Lab Meetings	5761	493
Total	60794	6301

Transcribed text and location data were integrated into a synchronized representation for the data mining and clustering phase. Table 1 provides a summary of the collected corpus in terms of the number of words and sentences per geographic location.

Generating Location-Dependant Frequent Vocabulary Patterns

An association rule-based data mining algorithm was used to implement location-dependant vocabulary prediction. A pattern is a set of items, or sequence of items that reoccur within a database. The probability that a transaction contains a pattern is referred to as its support. A pattern is said to be frequent if its support is greater than a predetermined minimum threshold and is said to be maximal if it has no other frequent super-pattern (Han & Kamber, 2000).

We used Borgelt's adaptation (Borgelt, 2003) of the Equivalence Class Transformation (Eclat) algorithm (Zaki, Parthasarathy, & Li, 1997), a parallel frequent pattern mining algorithm. The algorithm reduces the number of passes over the database and is highly efficient in generating maximal frequent patterns. In our implementation, the algorithm considers a sentential unit (i.e., a phrase, a sentence, or a fragment) as a transaction in order to generate frequent patterns.

Prior to further processing we implemented stop-word removal to eliminate core vocabulary items. Stop-words include words such as the, is, and, or, if, to, I, you, this, that, etc. which are thought to carry little semantic content. In addition to using stop-word lists widely used in natural language processing, such as the DVL/Verity Stop Word List (Defense Virtual Information Architecture, 2000) and the University of Glasgow Stop Word List (van Rijsbergen, 1979) we generated a speaker-dependant stop-word list containing colloquialisms and words such as like, you know, and wow that occurred often in the present corpus. These words and phrases were used across locations and carried little, if any, semantic content.

Following stop-word removal, we ran the algorithm using different invocation parameters and minimum support thresholds. These parameters included the frequent pattern size (i.e., one word, two word, etc.) and an option for generating only maximal frequent patterns.

Classifying Frequent Patterns into Discrete Levels of Predictiveness

Each lexical category in iconCHAT contains a one-layer deep lexical item set. For example, 'jeans' is contained in the category 'clothes' and similarly 'pizza' in the category 'food'. We have implemented a three-level differential shading scheme to help users scan and select the most appropriate vocabulary given their geographic context and current stage in message construction.

Decisions on differential shading of lexical items and semantic frames are based on frequency statistics observed within each location. The algorithm generates a rank ordered list of size-one (i.e., one word) frequent patterns. The support value of each frequent item is used to sort the list into one of three discrete levels: highly probable, probable, and neutral, conditioned on the user's current location and his/her current state in message construction. These discrete levels are visually represented using an arbitrarily defined grayscale shading scheme where the lightest items are those from the highly probable category to facilitate easy access. For example, 'coke,' 'fries,' 'drink,' 'hamburger,' and 'small' may be the top five (size-one) frequent times in a restaurant. Each item would have an associated support value that is used to determine whether the item should be categorized as highly probable, probable, or neutral.

Generating Quick Access Vocabulary Based on Frequent Patterns and Semantic Relatedness

To further improve vocabulary access we employed frequent patterns and semantic relatedness measures to populate a quick access vocabulary panel. Semantic relatedness is a quantitative measure of the degree to which two words are related. We used this measure to select closely related lexical items from the frequent pattern inventory. Several measures have been proposed to assess the semantic relatedness using WordNet (Fellbaum, 1998). WordNet is an online database in which lexical items are represented as a synonym sets. Lexical items in the database are linked to one another by approximately 30 semantic relations. Budanitsky and Hirst (2001) compared five methods of implementing relatedness using WordNet and found that the Jiang and Conrath (JCN; 1997) measure was most suited for natural language processing tasks such as ours.

1. We implemented a multi-step algorithm to populate the 3 x 8 icon quick access panel:
2. Select all size-one frequent patterns that have support values higher than the threshold.
3. For maximal frequent patterns of size two or greater, select all remaining items.
4. Given that the quick access panel can only accommodate a maximum of 24 icons, calculate the number of vacant icon slots after steps 1 and 2.
5. Calculate semantic closeness using the JCN measure (Pedersen, Patwardhan, & Michelizzi, 2004) for all pairs of size-two patterns that contain at least one element from step 1.

For each item in step 1, calculate the number of vacant slots that it can contribute to the panel based on its support. Fill these slots with item(s) that are most semantically related to it.

This algorithm yielded a list of lexical items that were used to populate the quick access panel for each unique geographic location.

Results and Discussion

In this section, we present the results of the algorithms described above and elaborate on how the findings can be leveraged to improve vocabulary access in an iconic AAC system. Interface adaptations are discussed in terms of the iconCHAT system to provide concrete examples of possible implementations. The general principles discussed, however, are applicable to AAC systems as a whole. We discuss issues of visual organization and navigation speed that influence message construction and their implications on human versus machine generated vocabulary selection.

Frequent Items in Each Location

A partial list of the 20 most frequent size-one patterns in the spoken corpus in each of the eight locations is presented in Table 2. Note that for some locations, the most frequent pattern has a relatively high support value (i.e., in bookstore, book has a support value of 69) while in other locations the most frequent pattern has a lower support value (i.e., in the kitchen, onion has a support value of only 39.5). This indicates that in locations such as the bookstore, the word *book* is likely to be part of a greater number of sentences, while *onion* may appear in fewer sentences produced in the kitchen. Recall that high support values influence the contribution weight of the item in the quick access panel.

Additionally the range of support values in the frequent patterns also differed by location (e.g., for Table 1, the bookstore support value range = 55.2; kitchen support value range =18.4). This range influenced the cutoff values for classifying items into the three discrete likelihood levels for differential shading. Frequent patterns that occur across multiple locations were typically core vocabulary items such as predicates (want, look, etc.), modifiers

Table 2
Size-One Frequent Patterns in Each Location and Their Support Measures

Bookstore	Research Lab	Classrooms	Clothing Stores	Electronics Stores	Grocery Stores	Kitchen	Lab Meetings
book-69.0	thing-47.7	time-50.0	Look-56.9	look-55.7	need-63.0	onion-39.5	time-44.1
look-41.4	people-45.5	thing-42.9	Nice-52.0	nice-28.6	look-40.7	cut-36.8	way-38.2
class-39.7	time-43.2	motor-35.7	Shirt-46.1	thing-28.6	make-37.0	use-36.8	try-38.2
stuff-34.5	work-34.1	way-35.7	color-36.3	stuff-24.3	want-37.0	carrot-34.2	little_bit-35.3
need-32.8	say-31.8	people-35.7	jacket-31.4	probably-24.3	thing-33.3	soup-31.6	different-32.4
thing-31.0	class-31.8	little_bit-28.6	stripe-30.4	little-24.3	Cheese-31.5	water-31.6	say-32.4
time-31.0	sort-29.5	stuff-28.6	Wear-29.4	small-22.9	ones-29.6	chop-28.9	class-29.4
read-25.9	speech-27.3	better-21.4	Stuff-26.5	work-20.0	stuff-27.8	little-28.9	record-26.5
use -24.1	little_bit-27.3	play-21.4	Blue-26.5	sort-17.1	use-25.9	need-28.9	minute-29.4
buy-20.7	use-25.0	oral-21.4	pants-25.5	different-17.1	cream-24.1	parsley-26.3	able-26.5
different-19.0	person-22.7	facial-21.4	Ones-24.5	speaker-17.1	chicken-22.2	add-26.3	easy-23.5
probably-19.0	different-22.7	sure-21.4	sale-24.5	want-15.7	probably-20.4	little_bit-23.7	recording-23.5
speech-19.0	disorder-20.5	disorder-21.4	different-24.5	sure-14.3	better-18.5	garlic-23.7	want-23.5
way-17.2	language-20.5	talking-21.4	white-23.5	little_bit-14.3	sure-16.7	pepper-23.7	data-23.5
sort-17.2	want-20.5	day-21.4	sort-22.5	player-14.3	ginger-16.7	boil-23.7	thing-23.5
sure-15.5	talk-20.5	couple-21.4	Light-22.5	big-12.9	little_bit-14.8	thing-21.1	file-23.5
actually-15.5	semester-20.5	want-21.4	probably-21.6	digital-12.9	plantains-14.8	fresh-21.1	sort-20.6
a_lot-15.5	lab-18.2	prepare-14.3	black-21.6	watch-12.9	list-14.8	way-21.1	make-20.6
funny-13.8	start-18.2	words-14.3	Thing-18.6	use-12.9	feel-13.0	vegetable-21.1	work-20.6
textbook-13.8	difficult-18.2	read-14.3	Little_bit-18.6	regular-12.9	eat-14.8	celery-21.1	maybe-20.6

Table 3
Impact of User-Dependant Stop-Word Pruning on Frequent Patterns in the Clothing Store Context

Pruned Frequent Patterns	
Generic Stop-Word	User-Dependent Stop-Word
like - 83.7%	look - 56.9%
kind – 69.6%	nice - 52.0%
know - 47.4%	shirt - 46.1%
look – 45.9%	color - 36.3%
yeah – 45.9%	jacket - 31.4%
nice - 43.7%	stripe - 30.4%
oh - 38.5%	wear - 29.4%
just - 37.0%	stuff - 26.5%
shirt - 34.8%	blue - 26.5%
color - 29.6%	pants - 25.5%

(a little bit, a lot), or generic nouns (thing, stuff). Perhaps these items should be made accessible in a different part of the interface such as in a context-independent panel of scroll buttons.

Factors that Influenced Algorithm Performance

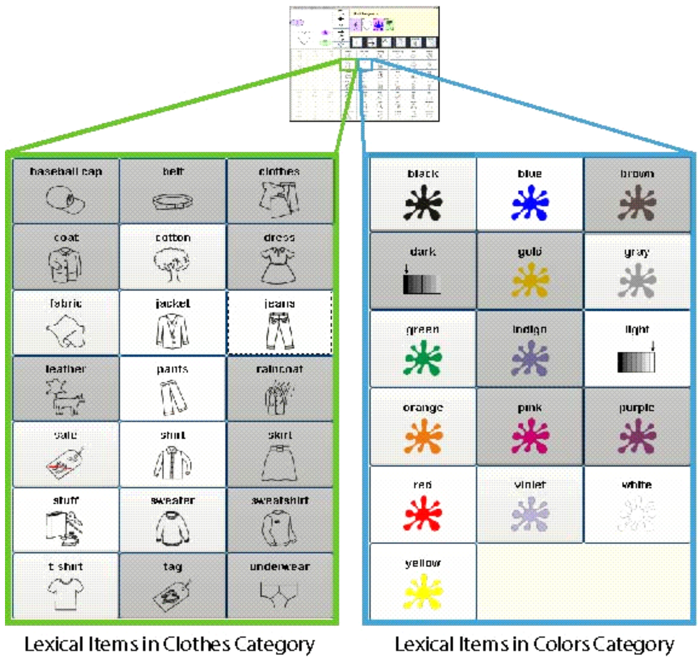
Given that stop-words occur often in spoken dialogue, they may alias as frequent patterns. As a result, other more content-laden vocabulary items may be pushed lower in the frequent pattern ranking or lost completely. In addition to using conventional stop-word lists, we found that a speaker-dependent list greatly enhanced performance (see Table 3 for a truncated list of size-one frequent items in the clothing store generated with and without user-dependant stop-words). An effective stop-word removal phase is especially important for iconCHAT since the natural language generation module attempts to minimize keystrokes by allowing the user to only select content words, leaving out function words such as *of*, *to*, and *the* during message construction.

Transaction size also had a significant impact on algorithm performance. Conversational speech typically contains less formal structure than written text. Incomplete grammatical constructions, fragments, lengthy trains of thought and backchannel exchanges often characterize typical spoken conversations. In contrast, communicative exchanges using iconCHAT fall somewhere between conversational dialogue and written discourse. Keeping these factors in mind, we experimented with varying lengths of sequential units to arrive at an ideal transaction size.

Leveraging Frequent Patterns to Provide Visual Selection Cues

For each location, size-one frequent patterns were classified into three discrete predictive levels within each lexical category. Predictive shading of category items enables the user to rapidly scan and sift through the most likely lexical items within each category. Figure 2 illustrates this feature in the *clothes* and *colors* categories for the clothing store context.

Figure 2. Location-dependant predictive shading for clothes and colors categories. © 2007, Rupal Patel. Used with permission.

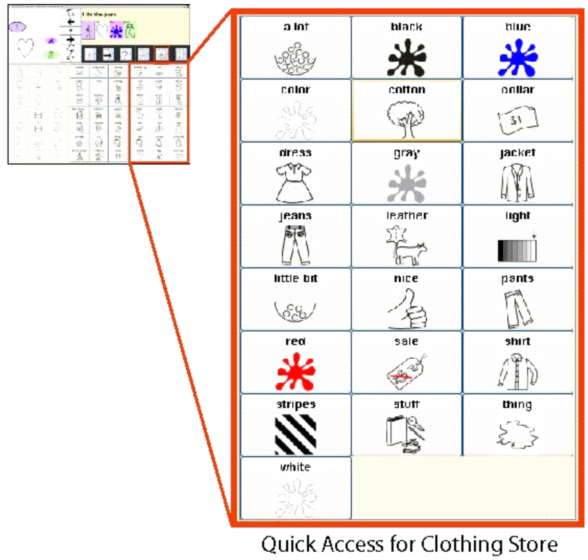


In the clothes category, the algorithm ranked *jacket* and *pants* to be among the most probable items and were thus represented at the brightest, most accessible level. Conversely, words such as *belt* and *dress* appear darkest and least accessible since they were judged to be neutral items for this user. Note that within each category, lexical items are alphabetically arranged as an attempt to assist in symbol search and promote early literacy skills.

Location-Dependant Quick Access Vocabulary

The quick access panel is aimed at further improving message construction ease. In other words, it helps reduce the number of clicks required to create a message by providing the most likely lexical items for a given context within a single panel (see Figure 3). Closer examination of the lexical items reveals their diversity with respect to their category and part of speech roles. In addition, an item such as 'dress', which was ranked 47 in the size-one frequent patterns, is promoted to the quick access panel containing only 22 members because support values and semantic closeness measures were considered together in this stage of analysis. Just as with differential shading, we anticipate that after repeated exposure, the user may gain insights into his/her own vocabulary usage patterns. The contents of the quick access panel may gradually change over time. For example, in the clothing store context, frequent items may change over the seasons. These changes occur over extended periods of time (e.g. weeks, months) such that the user is not confronted with a continual changing interface. Also note that the user still has access to all vocabulary items through the lexical category panel if the contents of the quick access panel do not meet his/her needs. Perhaps these seamless changes in the vocabulary content will promote receptive language and categorization skills.

Figure 3. Quick access panel for the clothing store location. © 2007, Rupal Patel. Used with permission.



Correlating Human and Algorithmic Rankings of Predictive Vocabulary

The Spearman ranked correlation measure was used to compare algorithm-generated vocabulary usage patterns with the user's perception of his patterns. Rankings were requested for the 10 most frequent size-one items in each location (see Table 4). Rankings for only nouns and modifiers were requested given our interest in assessing the effectiveness of predictive shading and quick access.

Inspection of the correlations across locations indicated that in general, locations with a large support value range in frequent patterns (i.e., bookstore) had higher correlations than those with a reduced support range (i.e., kitchen). From the user's perspective, it seems intuitive that a distribution of support values over a large range would allow more precise ordering. Conversely, a smaller range in support value distribution would make it difficult for the user to discern the importance of one item over another resulting in low or negative correlations. These discrepancies between user and algorithm rankings provide evidence that actual versus perceived frequency statistics often differ.

Trained clinicians, such as speech language pathologists, often make vocabulary choice decisions when programming AAC devices based on their own experiences and intuitions about a user's needs. Using an algorithmic approach to make these decisions based on actual frequency statistics along with clinical insights may improve communication efficiency and effectiveness. The algorithm may identify subtle, idiosyncratic patterns that are specific to that user thereby improving device customization. Since many users prefer a certain degree of control over their system rather than delegating decision making to the system (or to a clinician), a hybrid approach may balance these tradeoffs.

Outcomes and Benefits

This paper described an initial effort aimed at leveraging situational context for vocabulary prediction. The methodology

Table 4
Correlation Between User and Algorithm-Generated Rankings Size-One Frequent Patterns

Locations	Spearman Rank Correlation Measure
Bookstore	0.733
Research Lab	0.479
Classrooms	0.491
Clothing Stores	0.418
Electronics Stores	0.346
Grocery Stores	0.079
Kitchen	-0.369
Lab Meetings	-0.212

described mined vocabulary usage patterns of one able-bodied male user in various geographic contexts. The resulting context-dependant vocabulary patterns were implemented on the iconCHAT prototype system to illustrate how vocabulary access may be enhanced. While we began with an able-bodied user to ensure sufficient data on which to implement and assess the data mining algorithm, this open-set corpus had its drawbacks. The conversational topics, types of message constructions, and vocabulary choices were diverse and complex. Given that sentence constructions, conversational topics and frequent locations will vary on an individual basis additional algorithm tuning will be required in future implementations that operate on usage patterns of a typical AAC user. For some AAC users, the vocabulary set on their device may restrict the type and number of unique messages that can be created. These constraints may in fact improve algorithm performance.

Correlations between the user and algorithm-generated frequent pattern rankings suggest that decisions about vocabulary sets may benefit from a hybrid approach. In some locations the user's perception of frequent patterns were highly correlated with the actual statistics while in other locations the correlation was poor. A hybrid approach would entail the algorithm suggesting a vocabulary set (based on past usage patterns) from which the user or trained professional could choose the relevant items. Selecting the appropriate vocabulary is key to achieving improved communication success.

Another area that can significantly impact vocabulary access and thereby communication effectiveness is the user's understanding of his/her own usage patterns. Thus, if a user knew that frequent lexical items which are represented at the most accessible grayscale level were also likely to be in the quick access panel, s/he may be able to efficiently navigate to the desired item. In other words, knowing where to find a particular vocabulary item may accelerate access by reducing the number of keystrokes for message construction. Usability studies that assess the impact of situational vocabulary prediction on keystrokes savings, cognitive load and message construction accuracy and complexity are warranted.

Limitations and Future Directions

We plan to extend this work by collecting a more extensive corpus of message constructions produced by a group of able-bodied users as well as a group of AAC users within varied geographic contexts. Particular attention will be given to collecting sample utterances in a variety of conversational settings with multiple communication partners. This corpus will then be used to generate context-dependant vocabulary patterns for each user. Subsequently, we will evaluate the usability of discrete predictive levels of shading and the quick access panel.

We plan to broaden the methodology by building user-specific predictive vocabulary networks. Such networks would provide insight into organizational and navigational features that are beneficial across users. These insights can then be incorporated into future iterations of the interface design.

While this paper focused on the use of geographic context for vocabulary prediction, we are currently working toward harnessing other contextual cues such as time of day and conversational partner and topic. A significant challenge will be to integrate and visually represent vocabulary prediction using these varied contextual cues. Additionally, it will be important to monitor the use and effectiveness of situational vocabulary prediction.

Acknowledgments

This research is supported in part by the National Science Foundation (0083032) and the Department of Education, National Institute on Disability and Rehabilitation Research (H133G040051).

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