Learning User Models to Improve Wayfinding Assistance for Individuals with Cognitive Impairment

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Abstract
In this paper we discuss the benefits and challenges of designing customizable and adaptable applications for individuals to help improve their quality of life. As a supporting example, we describe our work learning user models to produce tailored pedestrian wayfinding directions for individuals with cognitive impairments.

Keywords
User modeling, cognitive impairments, wayfinding

ACM Classification Keywords
H.5.2 [User Interfaces]: User-centered design, K.4.2 [Computers and Society]: Social Issues – Assistive technologies for persons with disabilities

Introduction
There is growing recognition that applications should be designed to better match the needs and activities of individual users, rather than provide a “one-size-fits-all” usage model. It is especially important to consider user variation when designing applications in the healthcare domain, because an individual’s health condition can make it significantly more difficult to use certain designs. In contrast, a design tailored to an individual can provide significant improvements in usability [2].

Figure 1. Examples of direction types that differ by description of locations and message complexity

Researchers, including ourselves, have observed the need for customizable and adaptable design to support individuals with cognitive impairments in wayfinding, the process of traveling from one location to another [1,4]. Each individual's unique combination of abilities and disabilities creates a "universe-of-one" situation [3] where certain types of guidance may be understood and helpful while others may be confusing and even detrimental in wayfinding. A good design must therefore take into account such wide variation in potential users' ability to follow different types of wayfinding directions (see Figure 1 for examples) in different contexts, as well as their preferences over the presentation of directions.

The Importance of Customization

Current wayfinding supports assume a simplistic, default user model that takes little to no account of individual user preference. Written directions are worded without regard for how a user prefers to identify locations, so a person who prefers navigating by landmarks may find directions that refer solely on street names to be unhelpful. Maps can include labels for both streets and landmarks, but since space is limited, users are left with only the labels the map makers chose. Both are often difficult to follow by individuals with cognitive impairment because associating the physical environment with the symbolic labels is cognitively challenging.

Current navigation devices that use the Global Positioning System (GPS) also have poor support for user preference. Though they dynamically route a user based on current location, routing choices are limited to a few static options such as "fastest" or "avoid toll roads," under the assumption that all users respond to given directions the same way. Missing is the notion that some directions may be more difficult to follow for an individual, and subsequently that some routes consisting of such directions may be as well.

To overcome these limitations, we chose a framework by which we can incorporate individual user preference into wayfinding decisions as costs in a Markov Decision Process (MDP) [6]. This allows us to not only model preference for one type of direction over another at the same location, but to also compute lowest-cost routes from starting location to destination [5]. In related work, researchers have studied route preferences by observing expert drivers under the assumption that certain routes used by experts may be superior [7].

Adaptation to Complement Customization

We believe supporting customization can produce a better user experience for individuals in wayfinding, however it is not without challenges of its own. One such challenge is in eliciting those preferences. Self-report may be sufficient for some, but there are many individuals with cognitive impairments who may not have formed opinions about the different choices available, or who have difficulty communicating them. We could give the latter type of individual examples to rate, ideally in situ with a trial route. The problem is that due to the physical nature of wayfinding plus the time and effort involved in performing a trial route, the number of data points / preferences we can gather will be relatively small. Thus, there is a risk that a trial route is insufficient for gathering data representative of an individual's actual preferences.

A reasonable approach is to use trial data to seed a user model and incorporate subsequent observations of

Figure 2. N95 8GB phone used in our study. The keypad was divided into four input areas to request help (alternate direction), repeat directions, and switch between a photo-based direction involving a turn and a view from the turn facing the correct orientation (to disambiguate turn location).

wayfinding success and failure. We can then adapt models with additional data, and also learn participant tendencies or capabilities rather than simply preference. From the modeling perspective, we want to develop a model that can compute *direction difficulty*, the likelihood of a successful outcome when a user is presented with a certain direction, based on observations of a user in wayfinding.

Learning a Model of Difficulty

To test the feasibility of learning a difficulty model, we collected observations via a user study with 10 individuals (7 male) with cognitive impairment who were tasked with following a sequence of directions given by a prototype wayfinding application. The prototype ran on a Nokia N95 phone and supported audio, text, and image display (see Figure 2). Each direction was given as a participant approached an intersection of the predetermined route. We noted whether the participant followed each direction correctly, expressed confusion, or requested help.

For the analysis, we labeled each direction given to each participant as being difficult if the participant incorrectly followed it, showed signs of confusion, or used the Help button to request an alternate direction. We created a set of features, informed by this and previous studies, to describe each direction and then used linear regression to calculate several individual difficulty models. We used different training sets to train the models because we expected that a model trained on observations from only a single individual would overfit the relatively small number of data points, much like a single trial run might not yield a representative model of individual preference. The different models were:

- *Only p:* Each individual's observations were split into training and test sets, and linear regression was performed on the training set
- *Train:* Each individual's model was trained on all other participants' observations
- *Train + 1x p:* Each individual's model was trained on the union of the *Only p* and *Train* training sets
- *Train + 2x/4x/8x/10x/20x p:* Similar to *Train + 1x p*, but the individual's observations (their *Only* p training set) were weighed more heavily by being included 2/4/8/10/20 times, respectively

Results

Here we describe our initial approach to analyzing the collected data. We define a measure to quantify the models' performance, the *remainder incident rate*, as the percentage of observations among the directions in the participants' test sets ≥ a given predicted difficulty value. Intuitively, a good model produces remainder incident rate values that increase as the predicted difficulty rate increases. Then the correlation coefficient of predicted difficulty to remainder incident rate serves as an estimate of how well a model performs. Figure 3 shows the aggregate correlation coefficient values for all models across all participants, suggesting that the variation in performance decreases when we mix participants' observations but value an individual's data slightly more (4x and 8x in our data set). This occurs because using that individual's relatively small amount of training data causes overfitting, while not weighing it enough causes underfitting. Direct analysis of the incident remainder values for each model supports this, and we are collecting more data to make stronger claims of statistical significance.

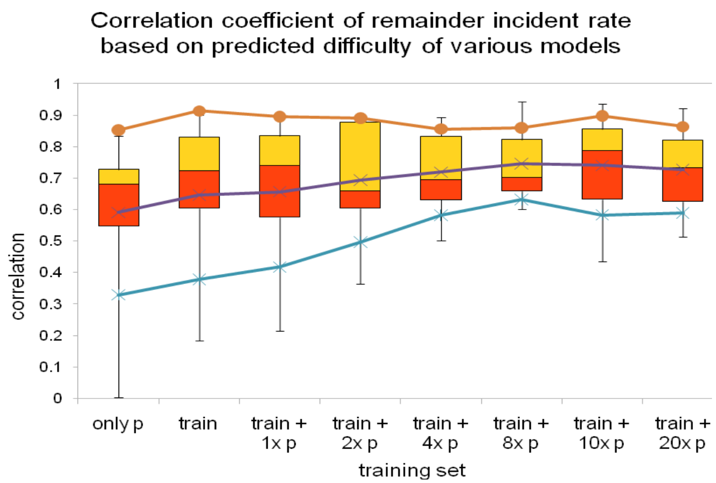

Figure 3. The correlation coefficient of remainder incident rate to predicted difficulty of our various models, shown for all 10 participants with median, 1st and 3rd quartile values represented by the boxes, minimum and maximum values as the whiskers, and the mean and one standard deviation above and below plotted as points.

Conclusion

Research has shown that user modeling can improve the usability of applications for individuals with unique requirements, positively impacting the quality of life for previously underserved users. Individuals with cognitive impairments would benefit from more customizable and adaptable wayfinding methods. As the time and effort involved in trial wayfinding runs limits the amount of training data that can be gathered for training an individual user's model, we investigated the performance of models trained on a combination of observations from both an individual and other users. Our initial results suggest that such a combination, with the individual's observations weighed somewhat more heavily, can predict wayfinding difficulty better than models trained only on other users or on just the individual. We are currently incorporating these findings into the design of an automated wayfinding system that will provide customized and adaptable directions and routes for individuals with cognitive impairments.

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