Toward Personalized and Context-Aware Prompting for Smartphone-based Intervention

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Abstract— **Intervention strategies can help individuals with cognitive impairment to increase adherence to instructions, independence, and activity engagement and reduce errors on everyday instrumental activities of daily living (IADLs) and caregiver burden. However, to be effective, intervention prompts should be given at a time that does not interrupt other important user activities and is more convenient. In this paper, we propose an intelligent personalized intervention system for smartphones. In our approach, we use context and activity awareness to time prompts when they will most likely be viewed and used. Our result based on real data collected using smartphone motion sensors demonstrate that the proposed approach can detect the time-frame of a user response with an average accuracy of 65% and reduce the inefficiency by 39% , on average, compared to different static time interventions which shows the possibilities and advantages of the proposed system to increase user satisfaction and response rate.**

I. INTRODUCTION

With recent advances in pervasive computing, wearable devices and smartphones are now being used in various applications such as activity monitoring [1], medication adherence [2], gait analysis [3], etc. One of the areas that these systems can be used is intervention. People who have cognitive impairment like dementia experience difficulty in everyday functional independence and therefore find it difficult to initiate daily tasks [4], [5]. Prompting technologies, that is, any form of verbal or non-verbal intervention delivered to the user, could potentially assist individuals with cognitive impairments [6], [7]. Basic and complex prompting technologies have been shown to increase adherence to instructions, decrease errors on everyday instrumental activities of daily living (IADLs), increase independence and increase activity engagement of individuals with cognitive impairment [8].

Prompting approaches are usually based on time, on location, or more recently on pauses between activities [6]. One key aspect of designing technology in this field is the difficulty of finding the most effective timing for prompt delivery. While most previous prompting technologies focused on delivery of prompts at times that are based on hard-coded rules, the main goal of this work is to develop a flexible personalized prompting system which offers the capability to learn prompt timings that are most effective for each individual and to adapt the timing to those situations.

The ultimate goal of a prompting system is to provide prompts at times when it would be most opportune for the user to receive them, and therefore respond to them. There are two main approaches for developing prompting systems:

1) Time-based Systems: these systems deliver prompts based solely on a pre-specified and inflexible time [7]. The most popular example of time-based prompting is Google calendar. Several studies have shown the effect of time-based prompting on people with intellectual disabilities and brain injuries [9], [10]. On the other hand, time-based prompts may be delivered when the user is engaged in another important task. A user may also become annoyed after hearing a prompt to do a task that has already been completed [6], [7].

2) Context-Aware Systems: context-aware prompting systems use the environment and the status of a user to find the effective prompting time. Location based prompting is the simplest example in this category which provides prompts based on the location of the user utilizing GPS, smart phone, or wireless sensor networks for example prompt when near a grocery store [11]. Similar to time-based prompting, the main limitation of location-based prompting is that the most effective time to prompt may not be dependent on the location of the user.

Activity-based prompts are another type of context-aware prompts which uses user's past and current automatically-recognized activity. These systems improved the prompting systems by prompting only when the user is experiencing a natural breakpoint, defined as the boundary between two adjacent activities [7], [12]. For example authors in [13] found that activity-based context-aware prompting helped people remember to take their medications and increased treatment adherence compared to time-based prompting.

Despite an improvement over classic time-based prompting methods, context-aware methods of prompting still have limitations because many tasks do not have clear boundaries. In addition, the best times for sending prompts to individuals varies for each person. Our work is novel in that it learns the best timings for each person in order to maximize user response and thus intervention effectiveness.

While intervention techniques are currently used by caregivers and individuals with different impairments to aid patients in maintaining their independence, it is still difficult to find convenient prompting times especially in the case of individuals with cognitive impairment. In addition, the time of prompting will vary between individuals and for an individual over time, possibly even on a daily basis. This may necessitate variable intervention time for the same person performing the same task [4], [6].

Motivated by these needs, we develop a personalized context-aware intervention system for smartphones. We hy-

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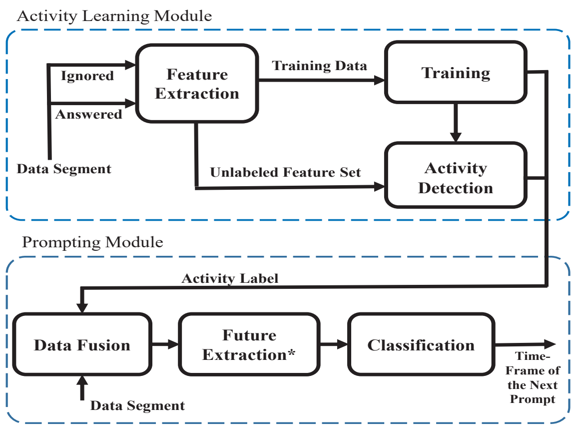

Fig. 1: An overview of the proposed prompting model. The activity learning module provides the daily activity labels for use in the prompting module. The prompting module predicts the most suitable time interval for the next intervention. *Features extracted in prompting module are listed in Table III.

pothesize that individual's response rate will vary depending on the daily activities they perform and other contextual factors such as day of the week, time, and location. To test our hypothesis we have three subjects respond to app-based queries about their current activity. We then apply signal processing and machine learning techniques to collected data to develop a personalized prompting system.

II. SYSTEM AND METHODS

We introduce an intelligent prompting model that takes advantage of advanced signal processing and machine learning techniques in order to provide a personalized, context-aware prompting experience. Our novel prompting platform aims to maximize the information delivery while considering the user satisfaction. Our system is based on a mobile platform that uses smartphone for gathering contextual data and interacting with user. An overview of the data processing pipeline is illustrated in Fig. 1. The processing pipeline consists of two key modules: an activity prediction module and a prompt decision module.

A. Activity Learning

As a part of our context-aware prompting model, we use a real-time activity learning (AL) algorithm to accurately predict the user's daily activities. The AL algorithm uses the readings from a combination of sensors embedded in the smartphone to extract discriminatory features. The details of the information collected from the smartphone are listed in Table I. It includes time, location, and motion based data. The data are further transformed into spatial and temporal features. In each sampling, a window of five seconds of activity is captured from the phone and through the interaction, the user will be asked to annotate the data segment with an activity label of their choice. When the user has opportunity he or she will respond to the query with an answer about their query. However, when the prompt does not appear at a time the user can be interrupted the user will not respond to the query (and thus the corresponding data segment will not be labeled). As a result the input data segment can be grouped into two: 'Answered' and 'Ignored'. At first, AL algorithm uses features extracted from the 'Answered' data to train a classifier. Once enough data is gathered (for our application we define this as at least 20 samples of each activity label), the trained classifier can be used to label the 'Ignored' data points. Finally, AL will either predict the activity category of the data (if the user did not respond) or incorporate the data as additional training examples (if the user did respond with an activity label). The details of activity learning module are explained in Section III-A.

TABLE I: Details of different data types used in AL module.

Data Category	Data Type
Motion	3-axis acceleration, 3-axis rotation, yaw, pitch, roll
Location	latitude, longitude, altitude
Time	hour, minute

TABLE II: The hypothetical observations from two users and the corresponding features used for distinguishing such behaviors.

	Hypothetical Scenario	Activity Type	Day of Week	Time	Location	Engagement Level
User 1	Work on campus ↓ vs Work at home ↑				✓	
	Mondays & Wednesdays ↓		✓			
	Walking to school ↓ vs Walking Home ↑			✓		
User 2	Jogging ↓ vs Watching TV ↑	✓				
	With friends ↓ vs Alone ↑					✓
	Weekends ↓ vs Weekdays ↑		✓			

B. Personalized Prompting

Our personalized prompting model takes into consideration the type of daily activity that the user is engaged in and also considers other contextual factors such as time, location, and the current level of engagement. Users may be more responsive during certain activities, or a certain period of the day. Response rates during certain days of the week might be lower (e.g., busy weekdays). In addition, unpredictable distractions can contribute to a lower response rate. The possible impact of each factor can vary among individuals. Table II shows examples of a few possible scenarios where different contextual factors may play a major role in determination of response rates. For instance, user 1 may show a higher response rate when working at home versus working on campus which emphasizes the importance of considering the user's location. In another hypothetical scenario, user 2 shows lower engagement when he/she is with company of friends which indicates the importance of considering the current engagement level in our prompting model. Based on these hypotheses, we compiled a short list of discriminative features (explained in Table III) that will be extracted from each data sample to be used in our prompting classification model. The output of our classifier is the most suitable time period for prompting.

III. VALIDATION

In this section, we elaborate on the experimental procedure and discuss the results. This experiment was reviewed

TABLE III: Details of the distinguishing features utilized in our proposed prompting model.

Feature	Description
Daily activity	activity labels given by activity prediction module
Engagement level	the time taken for the previous prompt to be responded
Location	GPS coordinates (latitude, longitude, altitude)
Time	day of week, hour, minute

(a) (b)

Fig. 2: Snapshots of AL application: (a) A prompt window asking the user to annotate his/her current daily activity (b) The prompt frequency setting view.

and approved by Washington State University Institutional Review Board.

A. Experimental Setup

Three healthy young adults were recruited to participate in our experiment. We used the Activity Learning application (AL) developed by [14] to collect data. Participants were asked to use AL on their phone for 7 days. As discussed before, AL collects 5-second windows of motion sensor data along with location, and time information in each sampling. After each sampling, a prompt will be shown on the screen, asking the user to choose an activity label from a list of daily activities for the collected data segment. The AL app allows the user to modify the list and add their own activity label. The frequency of sampling can also be modified, ranging from every ten seconds to every hour. Fig. 2 shows some screen-shots of the AL app. In this experiment, the sampling frequency of AL was set to ten seconds to enable a close to real-time data collection. Participants were instructed to respond to the prompts only when convenient and ignore the prompt otherwise.

B. Results

Over 1100 data samples marked with interactions were collected. Interactions include the prompts responded or directly rejected by the user. The collected data was used to extract activity learning dataset detailed in Table III. We further use motion and location-based data to extract 13 temporal and spatial features including maximum, minimum, sum, mean, median, standard deviation, mad, cross-axis correlation, skewness, kurtosis, signal energy, power, and autocorrelation. Using Weka 3.6 machine learning toolkit [15], a J48 decision tree classifier was constructed from

TABLE IV: The performance of the prompting model in predicting the time-frame of the next response.

-	Nearest Neighbor			Decision Tree		
	Precision	F-Score	AUC	Precision	F-Score	AUC
Sub 1	0.825	0.822	0.788	0.719	0.73	0.693
Sub 2	0.499	0.498	0.58	0.436	0.467	0.521
Sub 3	0.642	0.648	0.61	0.625	0.637	0.528
AVG	0.655	0.656	0.659	0.593	0.611	0.58

the annotated data segments. The activity learning model achieved 85%, 80%, and 84% accuracy on subjects 1, 2, and 3, respectively. The unlabeled dataset was fed into the J48 classifier to predict activity labels.

Our personalized prompting model was trained and developed per subject, using the activity labels (provided by AL module), time-based features, location data, and calculated engagement level in each data segment. Engagement level is calculated based on the response time of the previous prompt. Larger response time in previous prompt indicates lower engagement level. As mentioned, the output of our prompting model is the time window within which a response is expected. For our model, we considered four output labels (i.e., 5 minutes, 15 minutes, 30 minutes, and 1 hour). For instance the label '15 minutes' means that the corresponding prompt will receive a response within next 15 minutes. Note that the labels are mutually exclusive. In other words, only one label can be true for each prompt. By predicting the next response, our customized prompting module can be utilized to improve the response rate while minimizing the response time against the existing static prompting. We calculated the prompt labels for our dataset and used two standard machine learning algorithms (i.e., nearest neighbor and decision tree) to develop our prompting model.

Table IV lists the accuracy measures reported for the prompting model developed using the both algorithms. A model is constructed for each user using 10-fold cross-validation. On average, the nearest neighbor outperforms the decision tree model with an average precision, F-score, and AUC of around 0.65. Precision measures the fraction of identified labels that are relevant where recall measures the proportion of labels that are correctly identified as such. F-score is the harmonic mean of precision and recall. ROC is true positive rate vs false positive rate plot. The Area under the ROC curve (AUC) is an indication of the probability that the current model is making an informed decision.

In order to further demonstrate the effectiveness of our model, we compare the false positive (FP) and false negative (FN) rates of our custom prompt module versus static prompting. False positives occur when a prompt does not receive a response within the anticipated response time. For static modes the response time is constant while for the custom mode (the proposed model), it is determined by the output of the classifier. Similarly, false negative accounts for the missed opportunities where a response could be achieved but it was missed due to failure in sending one. In other words, high FP rate can be viewed as inappropriate prompting and high FN can be interpreted as poor

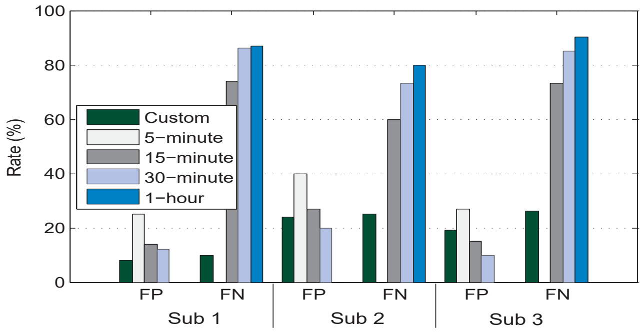

Fig. 3: The false positive and false negative rate of the proposed prompting model versus various static prompting modes. High false positive means poor response rate and high false negative means less efficient prompting.

TABLE V: Information gain of individual features.

Feature	Day of week	Time	Location	Engagement level	Daily activity
Information Gain	0.26	0.19	0.14	0.03	0.13

performance in terms of maximized information delivery. Fig. 3 illustrates the FP and FN results for each subject. Three fixed frequencies were chosen (identical to output labels of custom prompting model) to be compared against the proposed model. As it can be observed, our model is significantly superior to any fixed frequency modes. Fixed prompting modes fail to efficiently trade-off between FP and FN where lower frequencies (e.g., 1-hour interval) have very small FP rates but unacceptable FN rates. Similarly higher frequencies have higher FP rates.

We further investigate the impact of individual features using the Information Gain Evaluation algorithm and Ranker search method in Weka toolkit. It is a widely used standard feature selection method which measures the worth of a feature with respect to the change in information entropy given by:

$$IG(Class, F) = H(Class) - H(Class|F) \tag{1}$$

where H denotes the information entropy of data points associated with a certain class label. A higher score in Information Gain means easier classifications of the data points using that corresponding feature. Table V shows the average results over all the subjects. 'Day of week' and 'Time' have the most impact on our classifier. Engagement level fails to provide significant information. One reason could be not having a large enough dataset.

IV. CONCLUSION

In this paper, we presented a personalized context-aware prompting system using machine learning techniques than can potentially be used to help individuals with cognitive impairment by providing intelligent smartphone-based intervention. We demonstrated the capability of this approach in identifying appropriate times for intervention. The proposed algorithm outperforms the traditional time based prompting by increasing the response rate of interventions and decreasing inappropriate prompting (by 39%, on average).

In the future, we aim to address the existing limitations of the current approaches. To further investigate the effectiveness of the algorithm more participants and a larger dataset is required. Furthermore, as a future work, we plan to investigate the intervention techniques integrated with the smart-home prompting system to assess their impact on individuals with cognitive impairment.

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