Neurocomputational Modeling of Prospective Memory

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Abstract

Forgetting is in common in daily life, and 50-80% everyday's forgetting is due to prospective memory (ProM) failures, which have significant impacts on our life. More seriously, some of these memory lapses can bring fatal consequences such as forgetting a sleeping infant in the back seat of a car. People tend to use various techniques to improve their prospective memory performance. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks. The group of elderly participating in a group task may interact with each other before the date of the event and thus, a group member might be reminded by other group members of the group task. This thesis proposes a computational approach for determining the appropriate number of reminders and reminding method. The problem of determining the optimal reminding schedule is very complex due to many interdependent factors and uncertainty, it is thus difficult to build an integrated framework in which all the interdependent factors are concurrently optimized. Rather than modeling all the interdependent factors explicitly and then determine the optimal reminding schedule by an complicated combinatorial optimization, we try to connect all the inter-dependent factors indirectly and design novel heuristics to well approximate the optimal reminding schedule. In our approach, the reminding model will determine a reasonable number of reminders for a ProM task based on the predicted performance of the task. Guided by a reminder schedule function, the proposed model is also capable of generating an effective reminder schedule automatically. Moreover, the reminding model is able to make context-aware decisions regarding the reminding method. To evaluate the proposed reminding model, we conducted a preliminary user study and the participants felt that the reminders generated according to the reminding model are appropriate in terms of their number, schedule and reminding methods. The results also support that our approach provides a better overall experience and reminds more effectively than its control version.

Keyword: Prospective Memory; Group Task Reminding; Fuzzy Cognitive Map

I. Introduction

Nowadays ProM failure becomes quite prevalent. Studies have shown that ProM failures result in almost 50-80% of total daily memory problems [1]. The consequences caused by ProM failures could be quite serious, e.g., a patient forgets to take medications [2]. Prospective memory tasks have highly penetrated into people's daily life. The procedures of prospective memory task (ProM task) consist of encode and maintenance in ProM, then retrieval from ProM and performance later at a planned time or upon the occurrence of an event [3]. ProM aid systems have been applied by people in assisting their ProM task retrieval in many fields, from health applications targeting at brain injured or cognitively impaired people [4, 5] to general applications, like Google Calendar and AutoMinder [6, 7]. Over these decades, ProM aid systems are in progress of improving and evolving.

There are different types of ProM tasks and existing works on reminder systems only focus on individual tasks such as reminding elderly people to take their medicine. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks. For instance, seniors who enjoy being outside may like to play fun outdoor activities such as treasure hunts, bird watching, picnics, fishing, gardening and going to parks, lakes and many other places of interest. The group of elderly participating in a group task may interact with each other before the date of the event and thus, a group member might be reminded by other group members of the group task. Therefore, it is important to take into account the interaction between group members while designing an efficient reminding system for group tasks, which has not been addressed by any existing system and is focus of this chapter.

To design an efficient reminding system for group tasks, we need to address three key issues including 1) determining the appropriate number of reminders; 2) arranging effective reminder schedule; and 3) selecting appropriate reminding method based on context. This chapter refers to relevant theories and studies in ProM to cope with these three challenges. Specifically, based on the theoretical background of ProM, we thoroughly analyze the factors (including the potential interaction between group members) that will affect the ProM task performance. Based on the analysis, we propose a computational approach for determining the appropriate number of reminders and reminding method. The problem of determining the optimal reminding schedule is very complex due to many interdependent factors and uncertainty, it is thus difficult to build an integrated framework in which all the interdependent factors are concurrently optimized. Rather than modeling all the interdependent factors explicitly and then determine the optimal reminding schedule by an complicated combinatorial optimization, we try to connect all the inter-dependent factors indirectly and design novel heuristics to well approximate the optimal reminding schedule.

In our approach, the reminding model can determine an appropriate number of reminders for a ProM task based on the predicted performance of the task. Guided by a reminder schedule function, the proposed model is also capable of generating an effective reminder schedule automatically. Moreover, the reminding model is able to make context-aware decisions regarding the reminding method. To evaluate the proposed reminding model, we conducted a preliminary user study and the participants felt that the reminders generated according to the reminding model are appropriate in terms of their number, schedule and reminding methods. The evlauation results also support that our approach provides a better overall experience and reminds more effectively than its control version.

II. The Problem of Reminding Group Tasks

Under certain circumstances, we can observe the disadvantages of our reminder system, e.g., the failure in reminding, sending out redundant reminders, or disagreeable signal (e.g, some people's preference is sound reminder instead of visual reminder). Therefore, it is better to make enhancements to the generic reminder system to make it more reliable, optimal and adaptive. Hence, one of our main aims is to balance between the reliability and the annoyance as how many reminders should be issued to users for a specific ProM task.

Figure 1: Group elderly activities

There are different types of ProM tasks and existing works on reminder systems only focus on individual tasks such as reminding elderly people to take their medicine. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks as shown in Figure 1. For most senior citizens, group elderly activities can provide beneficial social contact with others. Assume that a group of people are participating in a group task (say picnics) in 10 days later and they have to also prepare for the group task before the event. The group of people also interact before the group task for other occasions such as daily exercise. Assume that we want to design a reminder system for such group activities, we can simply ignore the group interaction between the group members. In other words, we can treat each group member separately and direct apply existing approaches for determining the reminding schedule. However, such an approach will lead to many unnecessary reminders as one group member might remind some other group members.

Therefore, the comfort level of the group members will decrease dramatically due to the unnecessary annoyance.

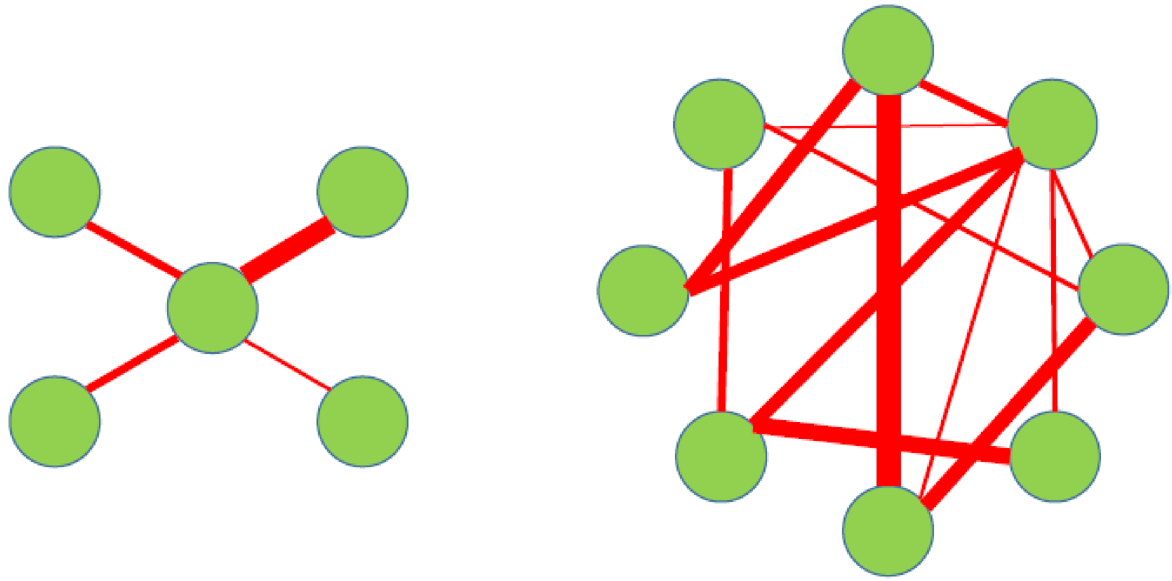

Figure 2 Different group interaction patterns. Each node represents a group member and the edges represent interactions. Different edge size represents different interaction frequency.

It is thus important to take into account interactions between group members including the frequency of the interactions. Moreover, we need to differentiate different group members as some group members might interact more with other group members (as shown in Figure 2). Thus, different group members might receive different number of reminders. Nowadays, with the development of technology such as Apps for tracking human's activities including the reminder system itself, information about interaction frequency is available.

Besides determining the number of reminders for each group member, the question of when to remind comes out because reminders are send out between the period of the first reminder and the time of executing the ProM task. Concerning that the reminder is a created cue to the ProM task, we have to think of another question how to keep the reminder salient and connected with the ProM tasks. Moreover, from the existing intelligent memory assists, such as Autominder with the adaptive feature [8], we can gain experiences. It is essential: 1) to develop a personalized user model to observe the users' behaviors. 2) to learn the users' preferences for each feature of the reminder plan. 3) to adapt the reminder plan to satisfy personal preferences as much as possible.

Therefore, our research questions boil down to how many times to remind, when to remind, and how to remind. As a consequence, our plan considers the number of reminders, the reminding schedule and the reminding way. To answer the first question, while too few reminders may fail, too many of them can be annoying. Hence it is crucial to take into account the interaction between group members to determine the number of reminders. Also it is important to issue the reminder at an appropriate time. A reminder for a task one month away may be too early. Meanwhile, a reminder issued just before the ProM task may leave the user in a hurry to perform the task. To select appropriate reminding method in terms of context, text reminders are appropriate at places which require silence. For noisy environments, more attention attracting reminding methods, e.g., vibration and sound are needed. Considering that a lot of work has already realized the function to attract attention and be context-aware at the same time, this chapter focuses on the first two research issues especially the first issue.

III. The Reminding Model for Group Tasks

This section presents our approach for computing the reminder plan for group tasks. We start with discussing the factors that can affect ProM performance and how the factors will affect the optimal number of reminders. Then we build a computational model for determining the number of reminder for each group member.

A. *Factors and Elements Identified from ProM Research*

Based on relevant ProM theories and studies, we find that the following key factors and contextual elements will influence the performance of a ProM task and how salient a reminding method.

Delay of ProM task. The delay of a ProM task refers to the time period from the encoding to the initiation of a ProM task. Generally, longer delay would reduce the performance of a ProM task [9].

Complexity of ongoing task. Ongoing tasks refer to the activities individuals are involved in at the time they need to perform their ProM tasks. The complexity of an ongoing task is defined as the relative number of required executive resources. In order to perform their ProM tasks, individuals need to shift executive resources occupied by ongoing tasks to the ProM tasks. Thus, as the complexity of ongoing tasks increases, it becomes increasingly hard for individuals to shift their executive resources and retrieve ProM tasks successfully [10]. That is, the complexity of ongoing task negatively affects the performance of a ProM task [11].

Relatedness of tasks. The relatedness of the two tasks becomes high when the ongoing task includes processing features which are related to the ProM task. If the ongoing task cannot draw attention towards evaluating the features of the ProM task, the relatedness is regarded as low [12]. To conclude, high relatedness between a ProM task and its ongoing task can result in easier retrieval of the ProM task. Hence better ProM task performance can be gained [12, 13].

Importance of a ProM task. The importance of a ProM task means its perceived importance by an individual. The importance of a ProM task can improve its performance as the strategic allocation of attention required [14]. Hence when the importance of a time-based ProM task increases, it will require more attention. Then the performance of the task would improve a lot. For an event-based ProM task, the retrieval is more spontaneous [15]. With the increase of its importance, less performance improvement will be experienced.

Motivation. Motivation refers to incentives or drive to perform a ProM task. Strong motivation will result in better performance of a ProM task. It is can proved from experiments in [16] and [17] that the performance of both time-based ProM tasks and event-based ProM tasks were enhanced with the present of social motives.

Age. Age is an important factor that can affect the performance of a ProM task. ProM of a person enhances first, and then degenerates gradually with the increase of age [18, 19]. Therefore, ProM task performance improves during childhood, then it will achieve at a peak point when grow up. Finally as people get older, ProM task performance will getting worse and worse [20].

Tolerance for disturbance. Tolerance for disturbance is defined as the degree to which one can tolerance the disturbance. If an individual has high tolerance to disturbance, a more salient reminding method should be chosen.

Noise level. Noise level refers to the noise level of the surrounding environment when the reminder is issued. For instance, if the ProM system is under a noisy environment, a more salient reminding method should be chosen to increase the probability that the reminder can be noticed.

The above mentioned factors influence each other. Some factors directly influence other factors or indirectly affect the relationship between another factor and the ProM task performance. Moreover, the importance of a ProM task can be reinforced with the presence of social motivation [21]. People's cognitive capabilities and mental functioning are gradually weakened with aging [24]. Accordingly, ProM will be deteriorated gradually. Hence, the degree to which age affects the ProM task performance is affected by other factors. With more complex ongoing task and lower relatedness between the ongoing task and the ProM task, there is a significant performance decline among the elderly compared with the younger [10, 22]. Contrarily, a higher performance improvement was observed among the older adults than the young adults [17].

B. *Determining the Number of Reminders for Each Group Member*

In order to determine the number of reminders for each group, we should apply existing approaches [25] to calculate the number τ_i' of reminders for each group member i. The calculating procedures are as follows: 1)We assume that the task is an individual task. 2)Then we aggregate the results to determine the number of τ_i , of reminders for each group member i considering the interaction between group members. In the following, we will firstly discuss how to compute the number τ_i' of reminders for each group member i with the assumption that the task is an individual task. The appropriate number of reminders for a ProM task should be determined according to the predicted ProM performance of the task. If the predicted performance is poor, more reminders will be generated for the task. On the contrary, fewer reminders will be generated if the predicted ProM performance is good. V_{perf} is the term used to predict the performance of a ProM task. It determines the joint-effect of the factors which will influence the ProM task performance. Figure 3 shows a visual representation of V_{perf} based on Fuzzy Cognitive Map (FCM) [23]. FCM is widely used to represent the cause-effect relationships among concepts in real-world systems.

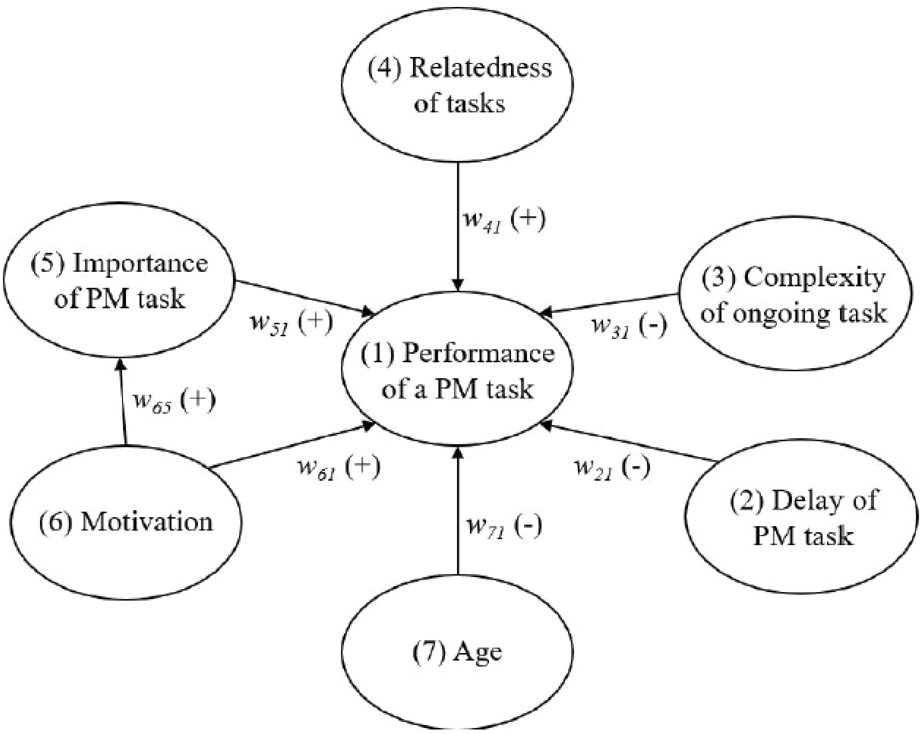

Figure 3 FCM for Predicting ProM Task Performance

Definition 1: V_{perf} can be defined as V_{perf} = {C,W}:

$$C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7\};$$

$$W = \{w_{21}(-), w_{31}(-), w_{41}(+), w_{51}(+), w_{61}(+), w_{71}(-),$$

$$w_{65}(+)\};$$

where

• c_1 represents *ProM task performance*: measuring the likelihood an individual will remember and perform a ProM task.

• c_2 represents *delay of ProM task*: measuring the length of the period from encoding to initiation of a ProM task.

• c_3 represents *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.

• c_4 represents relatedness of tasks: measuring the degree of relatedness between a ProM task and its ongoing task.

• c_5 represents importance of a ProM task : measuring the perceived importance level of a ProM task.

• c_6 represents motivation: measuring the incentive strength of a ProM task.

• c_7 represents age: measuring the degree to which age adversely affects the performance of a ProM task.

The plus (+) or minus (−) following a weight w_{ij} implies whether the weight is positive or negative. The weight values lie in the range [-1, 1].

Each concept in Vperf accords to one performance influencing factor, except c_1 which represents the ProM task performance. FCM both provides a way to capture the complicated relationships among identified factors and elements and a reasoning mechanism for inferring the ProM task performance and the salience level of reminding method. The weight values can be held by a 1×7 adjacency matrix W. If there is no direct arc from c_i to c_j , we have $w_{ij} = 0$. A 1×7 state vector C(t) is used to store the state values of the concepts at simulation iteration t.

Adaptation methodologies are used to adapt the FCM model (used in the last chapter) and adjust the weights. The state values of concepts in the next step are determined by both their current values and causal effects imposed by other concepts. To calculate the interim state vector, we can multiply the state vector C(t) with the weight matrix W.

$$\widetilde{C} = [\widetilde{c_1}, \widetilde{c_2}, \cdots, \widetilde{c_7}] = C(t) \times W$$

$$\widetilde{c_i} = \sum\nolimits_j w_{ji} c_j(t)$$

where $\widetilde{c_i}$ denotes the total sum of products of the state values of all concepts connecting to c_i and the weights of the arcs connecting them. The state values of the concepts in the next simulation step can be computed as the following equation:

$$c_i(t+1) = f_i(\widetilde{c_i}) = f_i(\sum\nolimits_j w_{ji} c_j(t))$$

where f_i denotes concept c_i's squeezing function. It converts the interim state value $\widetilde{c_i}$ of concept c_i into the new state value $c_i(t + 1)$, which is within required range [0, 1].

After the value of c_1 is stabilized, its value is used as a prediction for the performance of the ProM task. The number of reminders, τ , is derived by mapping the predicted performance to a corresponding number of reminders. If the value of c_1 is close to 0, i.e., the predicted performance is poor, it will be mapped to a larger number of reminders. On the contrary, if the value of c_1 is close to 1, it will be mapped to a smaller number of reminders.

After we compute the number τ_i' of reminders for each group member i assuming that the task is an individual task, we compute the number of τ_i of reminders for each group member i taking into account the interaction between group members. Intuitively, the number o reminders can be decreased as during the group members' interaction, a group member might be reminded of the task by some other group members. Furthermore, if a group member has more interaction with other members, the number of needed reminders can be smaller as the chance of being reminded by other group members is higher. Motivated by the intuitions, in the following we discuss how to compute τ_i based on τ_i' based on the interaction between group members.

We first formally define the interaction between group members using a graph G = (N,E,W), where N is the set of group members, E is the set of edges representing the interaction between group members, and W represents the interaction strength between group members, as shown in Figure 4. For an edge (i, j) between two group members I and j, $w_{i;j} > 0$ represents the frequency of interaction between two group members I and j. The higher $w_{i;j}$, more interaction between two group members i and j. A group member i's interaction strength IS_i can be defined as

$$IS_i = \sum_{j \in N} w_{ij}$$

which represents how frequently group member i interacts with others.

Then we can define the number of τ_i of reminders for group member i as

$$\tau_i = \lfloor \alpha \cdot \sum_{j \in N} \tau_j' \cdot \max\{\epsilon, \frac{e^{-IS_i}}{\sum_{j \in N} e^{-IS_j}}\} \rfloor$$

where $\alpha \in (0, 1]$ is used to reflect the intuition that the total number of reminders can be decreased in consideration of group interaction, $\epsilon \in (0, 1)$ is used to constrain the minimum number of reminders for each group member. The values of α and ϵ can be set by experimental tuning. We can see that with the increase of group member i's interaction strength IS_i, the number of τ_i of reminders for group member i will decrease.

C. *Reminder Schedule and Method*

The way to determine the appropriate number τ (τ is used instead of τ_i for ease of explanation) was explained above. Then the reminding model arranges the reminders into a reminder schedule, r schedule, according to a reminder schedule function. From Fig.4.4, it can be seen that the reminders are distributed over the reminding window, the whole window represents the time interval from the time of the first reminder to the starting time of the ProM task (Figure 4). The first reminder is defined by the user. While other reminders are automatically generated by the reminding model. The reminders are arranged in a way under which the reminding frequency gradually increases with the approaching of the starting time of the ProM task.

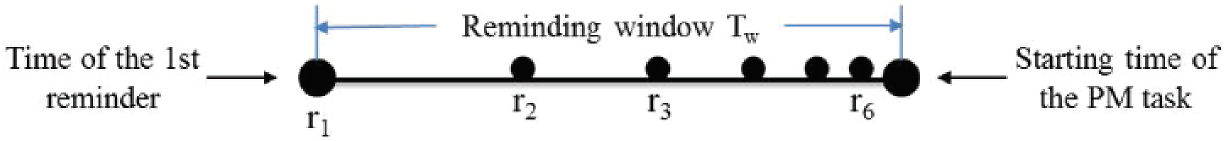

Figure 4 An Example of a Reminder Schedule

Under the assumption that the length of the reminding window is T_w and the total number of reminders is τ, the following reminder schedule function can be used.

$$T_k = (1 - e^{-\lambda k} + e^{-\lambda(\tau+1)})T_w$$

where $0 \leqslant k \leqslant \tau$ and T_k denotes the scheduled issuing time of reminder r_k ($r_k \in$ *r_schedule*). It can be easily inferred that the time interval between two consecutive reminders is decreasing.

The reminding model also determines an appropriate reminding method, r method, for each reminder r_k in *r_schedule*. It selects a reminding method according to the salience level required in a particular context. An appropriate reminding method should effectively attract attention without being intrusive. For each method, we can measure its effectiveness using the FCM model introduced before. Then we just choose the best reminding method.

IV. Experimental Evaluation

To evaluate our reminding model, we conducted a user study in naturalistic settings, involving 6 participants aged from 20 to 30. We assume there are 4 members in a group and the interaction strength is randomly generated. The values of α and ϵ are set to be 0.6 and 0.2 respectively. Our proposed reminder design (RMGT) was compared against 1) the reminder design without considering group interaction (RMIT); and 2) the reminder design manually generated by human beings (RMH). In the end, users completed survey questionnaires and sat through individual interviews.

The participants were requested to rate the appropriateness of the reminders generated according to the proposed reminding model. They rated on a scale from 1 to 10 and the ratings are summarized in Table 1. Generally, the participants felt that the reminders generated by our approach RMGT were appropriate in terms of their number, schedule and reminding methods. Each of these three aspects (number, schedule and reminding methods) received an average appropriateness rating greater than or equal to 8. Among them, ratings for reminding method RMGT have the largest mean and the smallest standard deviation, suggesting that the participants thought the reminding methods selected by the model were the most appropriate. The improvement of our approach RMGT over the other two benchmarks is statistically significant.

Table 1 Summary Statistics for User Rated Appropriateness

Aspect	**Mean**	**Standard Deviation**
RMGT	8.5	0.8544
RMIT	6.9	1.1354
RMH	6.7	0.8756

V. Summary

To our best knowledge, the reminding model proposed in this paper is the first-of-its-kind. Based on the theoretic background of ProM, this paper thoroughly analyzes the factors that will affect the ProM task performance and proposes a computational approach for determining the appropriate number of reminders and reminding method considering interaction between group members. To evaluate the proposed reminding model, we conducted a preliminary user study and the participants felt that the reminders are appropriate and our approach provides a better overall experience and reminds more effectively than its control version. Currently, the proposed reminding model only supports time-based ProM tasks. We are building up support for event-based ProM tasks and incorporating the consideration for travel time. The reminding model will be able to track locations and remind based on locations. Moreover, we will also consider improving customization of the proposed reminding model. The model will be able to cater to individual differences, since individual ProM task performance may respond to the six performance influencing factors differently.

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