A Task-Management System using Future Prediction Based on Personal Lifelogs and Plans

Toshiki Takeuchi
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
take@cyber.t.u-tokyo.ac.jp

Kyohei Suwa
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
suwa@cyber.t.u-tokyo.ac.jp

Hiroto Tamura
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
hiroto@cyber.t.u-tokyo.ac.jp

Takuji Narumi
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
narumi@cyber.t.u-tokyo.ac.jp

Tomohiro Tanikawa
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
tani@cyber.t.u-tokyo.ac.jp

Michitaka Hirose
The University of Tokyo
7-3-1 Hongo
Bunkyo-ku, Tokyo, Japan
hirose@cyber.t.u-tokyo.ac.jp

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Abstract
People who are busy generally have to manage a great variety of tasks. But sometimes, they fall behind in minor tasks and gradually, even without them noticing, a huge backlog piles up, far beyond the person's capacity to complete them well and on time. We proposed a task-management system that predicts a user's future state on the basis of the user's lifelog and plans, using a simple linear regression model. We implemented the system using a smartphone and estimated its usefulness with a user test. As a result, the users of our system saw their future diaries and tried to alter their current daily activities.

Author Keywords
Future prediction; task management; schedule management; lifelog

ACM Classification Keywords
H.4 [Information Systems Applications]: Miscellaneous.

Introduction
Task management is an important issue for people who are extremely busy. They must keep up with their current workload simultaneously planning future activities, and while also taking adequate care of their daily necessities. Task management, therefore, is an important research

Records	Action
92	Meal
46	Sleep
44	Take a bath
38	Laboratory
29	Breakfast
23	Dinner
22	Go to bed
22	Lunch
13	Housework
13	Last meal
12	Class
10	Programming
< 10	etc.

Table 1: The total number and content of each lifelog data.

Activity	Correlation
Task	-0.818
Leisure	-0.359
Movement	-0.237
Meal	-0.522
Sleep	-0.225
Task + Leisure	-0.874
Task + Sleep	-0.795

Table 2: Correlation between Plan and other activities.

theme[3, 5]. An individual can complete each small task separately. However, when small tasks pile up gradually, the total number of tasks increases beyond their capacity to complete them, and they fail to complete their tasks. In general, to complete any task, the maximum effort is required right before the task ends, but it is difficult to be aware of this. Besides, most people complete easy tasks first, leaving the difficult ones for later. To solve the problem, we propose a new task-management system using future prediction. The principal cause of task incompletion is that most people do not anticipate how much they have to complete in the future. The proposed system tells users the amount of time they will spend on their tasks, plans, and sleep in the future. They can then plan beforehand to avoid any complication predicted by the system.

The system predicts future tasks based on a reading of lifelogs. Lifelog is long-term log about one's life, stored as digital data[1]. A person's future state for tasks depends on their current plans and daily activities, and therefore, a task-management must consider personal features. Most of researches on lifelog has been limited to reading past logs efficiently by analyzing a large amount of lifelog data[2]. Recently, some of the researches has focused on future information and tried to predict the future from the personal data. Takeuchi et al.[4] focused on consumption. They predicted users' future consumption and tried to improve the users' financial balance. Although the accuracy of the prediction itself was not very high, users' finances improved because they used the information as a guide to change their income and expenditure toward an ideal model. We assumed that prediction using lifelogs would also be useful in task management. We have tried to predict personal activities in the future by using personal lifelogs and plans decided previously.

Prediction Based on Lifelogs and Plans

We asked six users to record their actions and the time of the actions for 14 days. We did not restrict the content of the logs and the users could record their lifelog freely. In the experiment, users recorded a total of 104 kinds of actions (Table 1). Among them, actions which had been planned in advance were many; there were also other similar actions that could be classified easily even if they had different labels in the logs. For example, Breakfast and Lunch and Dinner could be integrated with Meal. Thus we classified daily actions into six types. From now on, activity words that start with a capital letter refer to the activities defined as follows:

Plan Actions that are planned in advance: people cannot do any other action while doing Plan action.

Task Actions that require effort.

Leisure Actions for relaxation or that are hobbies.

Movement Actions to move to a place that is not related to Plan.

Meal Meals that are not a part of the Plan.

Sleep Sleep that is not a part of the Plan.

Next, we asked a user to record daily actions for 44 days. In this experiment, the user recorded his actions with the above six labels. After 44 days, we calculated correlation coefficients between the time of action and the time of Plan (Table 2). Generally, the time of action decreases when the time of Plan increases, and each correlation coefficient is a negative number. We see that Plan and (Task + Leisure) have the strongest negative correlation. A single regression analysis for Plan and (Task + Leisure) is the follow:

$$t'_{(Task+Leisure)} = -1.02 t_{Plan} + 666. \qquad (1)$$

t_{Plan} shows actual time of Plan and $t'_{Task+Leisure}$ shows predicted time of Task + Leisure. The time unit of t and

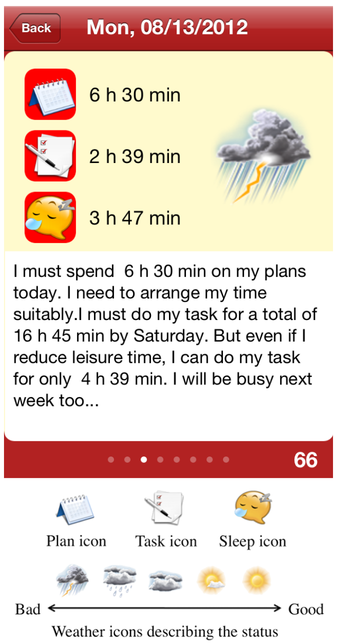

Figure 1: Future Diary.

t' is a minute. The coefficient of determination R^2, which provides a measure of how well future outcomes are likely to be predicted by the model, is 0.76449. As a result of an F-test, the p value is 0.74×10^{-12}.

We need to estimate time of Task only in order to predict future progress of tasks. Thus, we estimate the time of Leisure by averaging logged Leisure time per day and subtracting it from the estimated time of (Task + Leisure) to get an estimation of the time of Task.

$$t'_{Leisure} = avg(t_{Leisure}). \tag{2}$$

$$t'_{Task} = t'_{(Task+Leisure)} - t'_{Leisure}. \tag{3}$$

Time spent on leisure on weekdays and weekends would be different; we therefore use the average time of leisure logged on a weekday as the time of future leisure on a weekday, and use one on weekend in the same way.

System Implementation

We implemented the proposed system using a smartphone, web calendar, and a database server. For outdoor use, we used the iPhone as a lifelog input and feedback presentation device and developed an application, Future Diary. We implemented the server system with PHP and MySQL. To acquire a user's plan, we asked the user to write plans on a web calendar.

First, a user registers tasks on a smartphone. To support the progress of tasks, the user needs to register task information beforehand: a name, a deadline, and target time of a task should be input. Besides recording life activities on the smartphone, the user also writes plans on the web calendar every day. The task information and daily lifelog are stored in the database server. The server also gets the user's plan information from the web calendar regularly. Prediction processes are executed on the user's smartphone. When the user launches our mobile application, it receives data from the database server, predicts the future by using the above-mentioned method, and displays the result on the smartphone.

A user can see future information from the present day to a week later (Figure 1). Three icons and a weather icon are displayed on top to express hardness of the future state. The time on the right of three icons indicate actual time that a user will spend on the activity. For example, Figure 1 shows that a user will spend 6 hours (h) 30 minutes (min) on Plan, 2 h 39 min on Task, and 3 h 47 min on Sleep on Aug. 13, 2012. In addition, a text diary on the future day is automatically generated. Sentences prepared beforehand are selected and combined according to the total time of plans, the time the user should spend on tasks that day, the actual time spent, which the system estimated based on the user's lifelog. When the estimated task time is less than the desirable task time, the diary suggests that less time than usual should be spent on leisure and more time should be assigned to tasks.

User Study

We asked 12 users to record their lifelog for 31 days, and then asked them to use our system for 11 days. The purpose of this test was to investigate whether the system could change users' activities. However, it was difficult to compare logs with and without the system's feedback since the task conditions were largely different. Thus, after the term of the test, we conducted a questionnaire survey of the users to investigate whether they had changed their minds and activities. The following questions were asked in five-point scale:

Q.1 How did the time spent on plans, tasks, leisure, and sleep change?

Q.2 How useful was the system?

Q.3 How accurate was the future prediction?

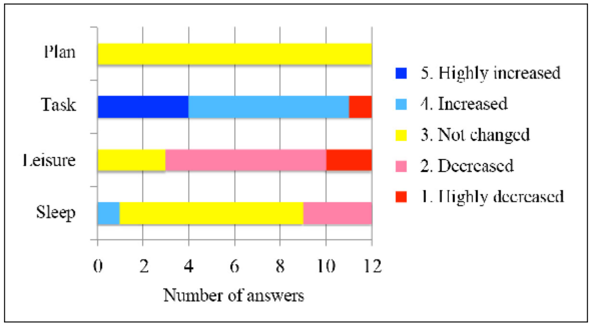

Figure 2: How did the time spent on each activity change?

Figure 2 is related to the first question. According to this result, most of the users were willing to increase time allotted to tasks and decreased leisure time. We think that users noticed that they could spend less time on their tasks than expected by getting a concrete vision of their task progress, and they increased the task time in order to make up for the deficit.

The average of answers to the second question is 4.2. The results show that the users became conscious of their future status with the system and altered their daily actions in order to complete their tasks. The result of the second question indicates that our application was useful to support the users' task progress. The application revealed that they sometimes wasted their time.

The average of answers to the third question is 3.6. Almost half the number of users felt the prediction provided by the system accurate, though the others felt the prediction was neither right nor wrong. We know that the accuracy of prediction was not high, but we believe that the system has some good effects.

Conclusions and Future Work

We proposed and implemented a new task-management that records lifelogs and plans with a web calendar, predicts future state of tasks, and shows them to a user in a text diary style. 12 users who used our system answered that they tried to increase time spent on Task and decrease time on Leisure. The prediction method in this research was simple and naive, but it had some positive results. We believe that we showed the potential of task management using personal lifelog-based prediction.

Improving prediction is a future task. The method used for prediction was naive, and therefore, users sometimes encountered strange predictions. We want to use another model such as a neural network model or a Bayesian network model, and improve confidence in the system.

References

[1] Bell, G., and Gemmell, J. *Total Recall: How the E-Memory Revolution Will Change Everything*. Penguin Group (USA) Inc., 2009.
[2] Gemmell, J. MyLifeBits: A Personal Database for Everything. *Communications of the ACM 49*, 1 (2006), 88–95.
[3] Ohmukai, I., and Takeda, H. Social Scheduler: a Proposal of Collaborative Personal Task Management. In *Proceedings of IEEE/WIC International Conference on Web Intelligence* (2003), 666–670.
[4] Takeuchi, T., Narumi, T., Nishimura, K., Tanikawa, T., and Hirose, M. Receiptlog Applied to Forecast of Personal Consumption. In *16th International Conference on Virtual Systems and Multimedia (VSMM)* (2010), 79–83.
[5] Whittaker, S. Supporting Collaborative Task Management in E-mail. *Human-Computer Interaction 20*, 1 (2005), 49–88.