LifeLog-based Estimation of Activity Diary for Cognitive Behavioral Therapy

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Abstract
Cognitive Behavioral Therapy (CBT) shows promise for the effective treatment and prevention for depression. During the long-term treatment with CBT, users (e.g. patients with depression) are given some kind of homework in their daily lives to self-monitor their thoughts and behaviors by using some techniques taught by therapists (e.g. doctors) in the face-to-face session. In this paper, we present an application to support users to do their homework, especially self-monitoring of their behaviors. By collecting lifelogs of them via smart phones, the application estimates their behaviors (activities) based on their lifelogs and shows the results to support self-monitoring by themselves.

Author Keywords
Cognitive Behavioral Therapy (CBT); Depression; Self-Monitoring; LifeLog; Smart Phones.

ACM Classification Keywords
J.3 [Computer Applications]: Life and Medical Sciences - Health

Introduction
Depression is costly especially in established market-economy countries[1]. Cognitive Behavioral Therapy (CBT), a form of counseling or talking therapy, shows promise for the effective treatment and prevention for depression[2]. CBT fo-

cuses on changing one's thoughts and behaviors in order to change her or his feelings because changing the thoughts and behaviors directly is easier than changing the feelings directly, and the feelings can be changed indirectly by changing the thoughts and behaviors. In the treatment with CBT, users (e.g. patients with depression) and therapists (e.g. doctors) have several face-to-face sessions. In these sessions, therapists teach users some CBT techniques to self-monitor their (automatic) thoughts and behaviors, and to change them. Users are given homework to practice the techniques in their daily lives to self-monitor and change their thoughts and behaviors by themselves. By mastering the techniques to change their thoughts and behaviors, users will be able to change their feelings.

However, homework to practice techniques is not always easy, especially for users with depression because they are depressed. Towards this problem, we have implemented a platform to support CBT for depression using smart phones[3]. Some of us are the "real" therapists of CBT, and their knowledge is reflected in the design of the platform. Users can practice the techniques via smart phones anytime and anywhere in their daily lives, and the progress of practice is recorded on smart phones and shared within therapists via the Internet connectivity of smart phones. Therefore our platform helps not only users, but also therapists.

Recording (filling in) the "activity diary", which is one common form of homework used in CBT, requests users to record their activities (behaviors) in their daily lives on worksheets (like [4] and Figure 1). By recording the activities, users can remember their activities, and by viewing the worksheets with activities, users can review their daily lives. However, this homework is also difficult for many users because they have to remember their daily lives.

In this paper, we introduce a new application to support users to make "activity diaries." This application collects lifelogs of users via smart phones, and estimates their activities based on the lifelogs. By showing the estimated activities, users can be helped to record "activity diaries" even when they cannot remember some activities of their daily lives.

Date							
Time	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
01:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
02:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
03:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
04:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
05:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
06:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
07:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
08:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
09:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
10:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
11:00	(%)	(%)	(%)	(%)	(%)	(%)	(%)
12:00							

Figure 1: An Example of Activity Diary Worksheet

Activity Diary for CBT

In homework of CBT, users write the activities into the time slots of the worksheets like Figure 1; in other words, users divide the time slots when the activities are changed. The activities listed below are the examples users may write:

- Sleep
- Rest
- Meal
- Bath / Shower
- Work / Study
- Shopping
- Exercise

The spaces enclosed in parentheses with "%" are the spaces to write the feelings during the activities. The value may represent the positive feeling such as pleasure or accomplishment felt by the subject during the activity. In some treatments with CBT, users have to write such value. (In this paper, we don't focus on the feelings.)

Application to Edit Activity Diary

We designed and implemented an application for smart phones to edit an activity diary. We choose iPhone (Apple Inc.) as the smart phones to implement the application because other applications of our platform are implemented on iPhone.

The application collects lifelogs of the user and estimates the activities based on their lifelogs. (In current implementation, the engine to estimate the activities based on their lifelogs is implemented as a server-side program, so the application for smart phones needs to integrate with the engine via the Internet. We have a plan to merge the engine into the application for smart phones.) The application mainly analyzes location of the user by using DBSCAN[5], a well-known spatial clustering algorithm, to find clusters where the user stayed for a while. Before applying DBSCAN, the application converts the logs of location to time-periodical logs because the API to observe location on iPhone is not designed for time-periodical observation. In this conversion, this application removes less-accurate logs. By setting the interval of time-periodical logs to 1 minute, the application gets $1440 (= 60 \times 24)$ logs of location for each day. Then, the application applies DBSCAN to the converted time-periodical logs of location with two parameters Eps and $MinPts$. Eps represents the minimum distance between locations to be grouped into the same group, and $MinPts$ represents the minimum number of locations for a group to be treated as a cluster. Clusters that include the same location may be merged, and the locations that are not included in any cluster are treated as noise. The application uses 150 m as Eps and 30 as $MinPts$ to extract clusters. Using 30 as $MinPts$ means to extract clusters where the user stayed for more than 30 minutes at a time. However DBSCAN itself cannot treat temporal sequence, so DBSCAN may extract clusters where the user stayed for less than 30 minutes at a time (e.g. where the user stayed for 15 minutes in the morning and 15 minutes in the evening of the same day). The application treats such clusters as noise. Finally, the application gets cluster identifiers (noise is treated as a special identifier) for every minute.

The first day of use, the application cannot estimate activities, but can estimate time slots that the user stayed in the same cluster, or moved between clusters. The application converts the cluster identifiers for every minute to the cluster identifiers for every hour by selecting the most common cluster identifier in 60 minutes because the traditional activity diary worksheets like [4] and Figure 1 are divided hourly. Then the application just shows the time slots divided based on the clusters (Figure 2 (a)). The user can edit the activity by selecting from 16 activities (Figures 2 (b,c)), which we categorized various activities into based on the knowledge of the "real" therapists. Of course, the user can edit the time slots by adding, moving, and deleting the border of the time slots. Through these processes, users can record active diaries.

On and after the second day of use, the application can estimate activities based on the history of the cluster identifiers and the activities which the user selected before (Figure 2 (d)). The application uses Support Vector Machine to estimate activities, by using the cluster identifiers, the information of the time slots (the hour, the day of the week, etc.), and the activities selected by the user in previous days as the training data, and also using the cluster identifiers and the information of the time slots of the target day as the sample data. If the estimated activity is correct, the user needs only to click on "OK" icon to finalize the activity

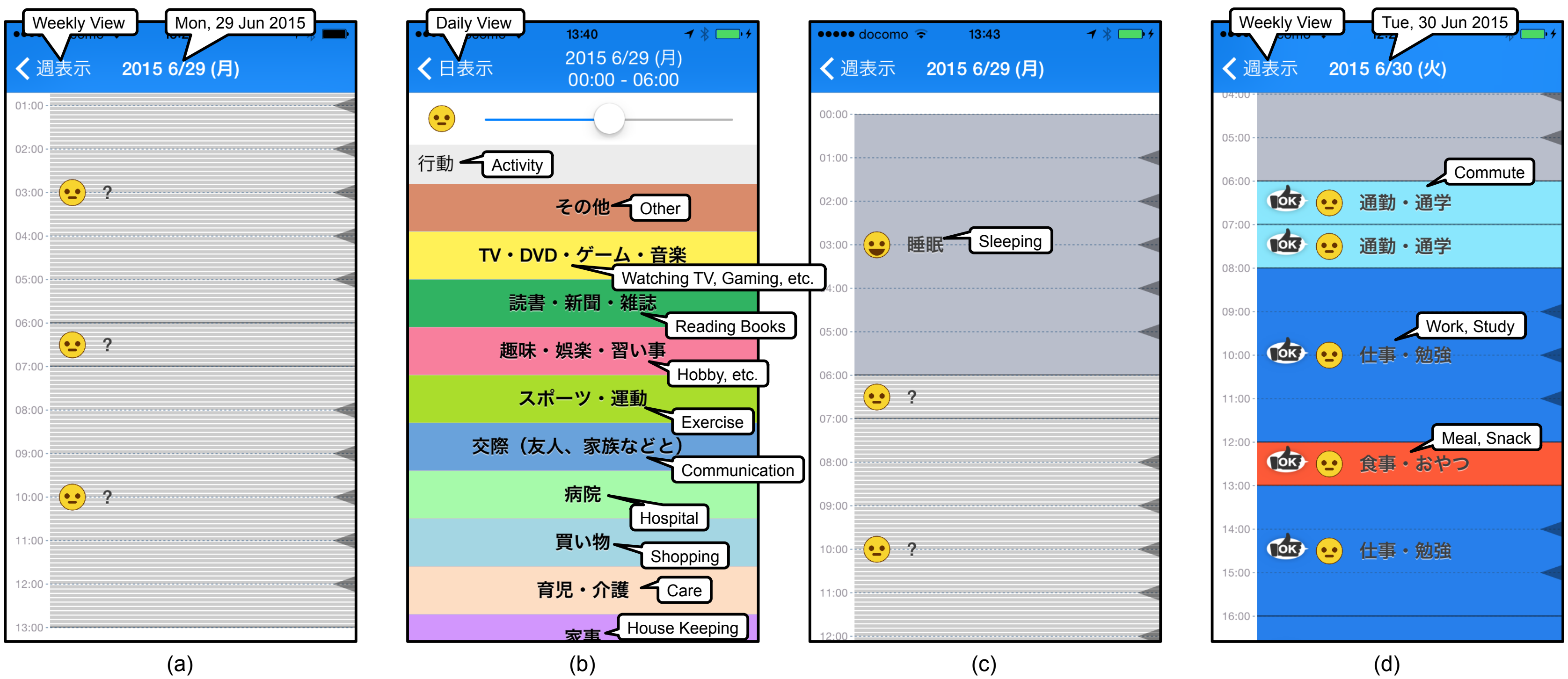

Figure 2: Screenshots of the Application. (a) The first day of use, the application cannot estimate activities, but can estimate time slots that the user stayed in the same cluster, or moved between clusters. (b) The user can edit the activity by selecting from 16 activities. (c) The selected activity will be set. (d) On and after the second day of use, the application can estimate activities based on the clusters and the history of activities that the user selected before. If the estimated activity is correct, the user needs only to click on “OK” icon to set the activity. Otherwise, the user can edit the activity. The smile marks in all screenshots are the feeling levels that the user can input manually.

	Estimation Accuracy	
	Weekdays	*Weekends*
1st. week (Day 2 - Day 7)	65.3 %	42.7 %
2nd. week (Day 8 - Day 14)	65.7 %	49.5 %
3rd. week (Day 15 - Day 19)	66.7 %	54.9 %

Table 1: Results of the Preliminary Evaluation

record.

Preliminary Evaluation

Before experimenting the application, we evaluated the accuracy of our estimating algorithm. We collect the lifelogs and activity diaries from 9 participants (2 females and 7 males, 2 students, 1 homemaker, 1 part-time worker, and 5 office workers, 1 of the 5 office workers is one of us) for 19 days. All the participants are not patients with depression. The lifelogs are collected via smart phones in the same way of the application, but the participants write their activity diaries on paper-based worksheets, not via the application, because the preliminary evaluation has been done before the implementation of the application. By comparing estimated activities from the lifelogs and the activities on paper-based worksheet, we evaluate the accuracy day by day.

Table 1 shows the results of the accuracy of the estimating algorithm. The result of day 1 is not included because our algorithm cannot estimate the activities at the first day of use. The accuracy of weekdays is higher than the accuracy of weekends. We considered that it is caused by the difference of the number of days and the variety of the activities of weekends. Both of the accuracy of weekdays and weekends has improved with time.

Conclusion

In this paper, we introduce the application to record and edit the activity diary. By collecting lifelogs of users via smart phones, the application estimate their behaviors (activities) based on their lifelogs and show the estimated results to users to help editing the activity diaries. We have just started an experiment of the application with some participants (without depression), and will evaluate the performance of the estimation algorithm and the usability. After the experiment, we have a plan to integrate the application with our platform[3] in order to be used by patients with depression.

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