

Recording Daily Health Status with Chatbot on Mobile Phone - A Preliminary Study -

Haruhisa Maeda, Sachio Saiki, Masahide Nakamura
Graduate School of System Informatics, Kobe University
1-1 Rokkodai, Nada, Kobe, Hyogo 657-8501, Japan
Email: haruhisa@ws.cs.kobe-u.ac.jp, masa-n@cs.kobe-u.ac.jp

Kiyoshi Yasuda
Faculty of Informatics, Osaka Institute of Technology
5-16-1, Omiya, Asahi, Osaka, 535-8585 Japan
Email: fwkk5911@mb.infoweb.ne.jp

Abstract—To support in-home long-term care, we are studying techniques of *mind sensing*, which externalizes internal states of elderly people as words through conversations with agents or robots. We previously developed the *memory-aid service*, where a chatbot on a mobile phone autonomously talks to elderly people, to record their conditions, events, and memorandums. During experiments with healthy elders, we found that they regularly talked to the chatbot about *health status*, such as weight and blood pressure. This motivated us to use the mind sensing as an affordable and practical means to record daily health status.

In this paper, we present a method where individual users can declare health metrics of their interests, and record them through the mind sensing. Specifically, for each user-defined metric, the chatbot asks the user the current value of the metric at the designated time. The text conversations are then put in a data mining process to extract time-series values of the metric. The time-series data is finally visualized as a graph, with which the user can review the health status. Our preliminary experiment shows that individual health metrics can be recorded and visualized successfully even without “connected” measuring instruments.

Index Terms—smart healthcare, mind sensing, data mining, chatbot, conversational agent, IoT

I. INTRODUCTION

According to the Japanese Government, the number of Japanese people over the age of 65 is 35.15 million in 2017, which is 27.7% of the total population [1]. The number continues to increase and will reach 40% of the total in 2050. Similar situations are observed in most developed countries in the world. Such a super-aging society causes a chronic shortage of human resources, nursing facilities, and the cost of social security. The Japanese government is therefore shifting the policy from the conventional facility care to *in-home long-term care*. It is ideal for all elderly people to live in their beloved homes. However, they generally face various difficulties in daily life due to the decline of physical and cognitive functions. Also, home care would pose a heavy burden on family caregivers. In order to support these elderly people at home, the *assistive technologies* have been studied and developed in various organizations in recent years.

A promising technology to support the in-home long-term care is the *elderly monitoring system* using ICT. Exploiting sensors, wearable devices, and smart home technologies, the system tries to *recognize* daily activities of elderly at home. Various methodologies have been studied, for example,

the method with ambient environmental sensing [2] [3], the method with accelerometers of mobile phones [4], the methods with wearable sensors [5], and the method using a smart home with indoor positioning and power meters [6].

On the other hand, monitoring with sensors has a limitation that it detects only *externally observable events*. To perform person-centered home care, it is also important to recognize *internal states* of elderly people. Here, the internal state refers to a status of a person that cannot be observed externally, including moods, pains, conditions, desires, and intentions. Since the internal state is directly linked to human health, it is important to monitor within the home care [7]. However, the internal state is usually assessed through inquiries and counseling by experts. Hence, it is challenging to monitor the internal state regularly at home.

In order to cope with the limitation, our research group is studying techniques of *mind sensing* (“kokoro” sensing in Japanese [8]). It externalizes the internal states of elderly people as “words” through conversations with agents or robots.

In our previous study [9], we developed the *memory-aid service*, exploiting a mind sensing method with a *chatbot* on a mobile phone. Triggered by time or an event within a smart home, the chatbot asks a user (i.e., elderly person) a question that externalizes the internal state as words. As the user answers the question by text (as well as voice and images), the conversation is automatically recorded in a database with a timestamp. The service then provides the *retrospective process*, where the user can review, correct, classify and search the recorded information of own at any time. Thus, the service is designed for the memory-aid purpose of healthy elders as well as people with cognitive impairment.

To evaluate the practical feasibility, we are experimentally operating this memory-aid service within actual households of healthy elderly people. Then, we found that they often talked about their *health status*, such as pains, weight, blood pressure measurements and the number of steps walked. Of course, the metrics of interests and the way of recording varied among individuals. However, recording such health status on a daily basis is quite important and should be promoted more explicitly. Although there exist “connected” devices measuring such health data online, they are not yet adopted widely by elderly people, and would be intrusive for their daily life. This motivated us to use the mind sensing as an affordable and

practical means to record daily health status.

In this paper, we investigate a method where individual users can declare health metrics of their interests, and record the metrics through the chatbot-based mind sensing. Specifically, for each user-defined metric, the chatbot asks the user the current value of the metric at the designated time. As the users respond with the value, the conversation is recorded in a database. Applying data mining process in the recorded messages, we extract time-series values of the metrics. The time-series values are finally visualized as a graph, with which the user can review the health status.

We have conducted a preliminary experiment that visualizes health status from the mind sensing records of two elderly people. The visualized metrics include blood pressure measurements, consumed calories, the number of steps of walking, the weight, the health condition, the time of wake up and go to bed and the record of defecation. In the time-series graphs, we observed that changes in health status are well observed. Thus, the individual health metrics can be recorded and visualized successfully by the proposed method with the chatbot-based mind sensing.

This study has been approved by the research ethics committee of Graduate School of System Informatics, Kobe University. Written informed consent was obtained from subjects for publication of this paper and accompanying images.

II. PREVIOUS STUDY: MEMORY-AID SERVICE [9]

A. Overview and System Architecture

In [9], we have developed the memory-aid service to support elderly people at home who are anxious about age-related forgetfulness, as well as cognitive impairment. The key idea is to provide an *external memory* for a user (i.e., an elderly person), so that the user can easily record whatever important for the user, and can retrieve the recorded information at any time. Major challenges were (1) how to encourage the user to record the essential information (including the internal states) in the external memory, and (2) how to use and maintain the recorded data for better quality life of the user.

Figure 1 shows the system architecture of the memory-aid service, consisting of the following two functionalities:

Chatbot-based Mind Sensing is a mechanism that externalizes and records the information in user's mind, through conversations with a chatbot on a mobile phone. Triggered by time or an event issued by an external system, the chatbot autonomously asks a question to the user. In [9], we integrated the activity recognition system [2] with SensorBox [10], in order to generate context-aware questions. Typical questions include "What are you doing now?", "How are you feeling today?", "Did you sleep well?", "What did you do today?" and "Where do you want to go?"

As the user responds to the chatbot by manual text input or the speech-to-text input of the mobile phone, the text message is sent to Web-API, and recorded in a database with a timestamp. Moreover, regardless of the questions, the user can spontaneously talk to the chatbot to record any information, such as memorandums, schedules, appointments, and thoughts.

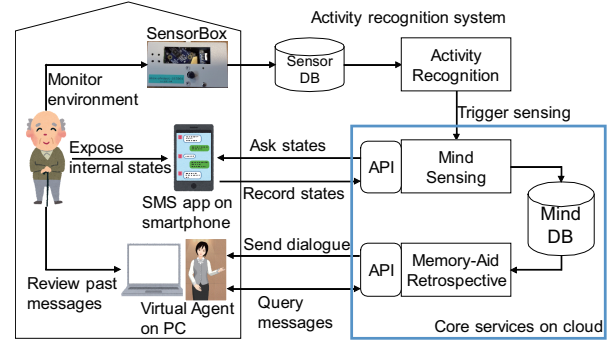


Fig. 1. System architecture of memory-aid service [9]

Memory-Aid Retrospective is an application that provides an opportunity where the user can *look back* the recorded information. Exploiting voice interaction with a virtual agent [11] and intuitive graphical user interface, the user can perform two types of retrospective processes on a PC.

In the *short-term* retrospective process, the system displays the list of *fresh* messages recorded within one day before now. While viewing the list at the end of the day, the user can remember what happened today. To maintain the quality of the data, the application tells the user to correct typos and errors in the existing records, or to add supplementary messages if necessary. Moreover, for every record, the user can associate user-defined *categories* that explain the type of the information.

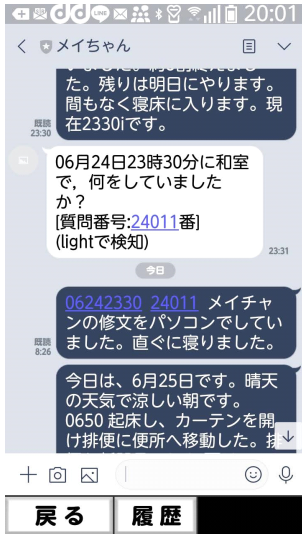
In the long-term retrospective process, the user can view and search all the existing records. By simple user interface assisted with the virtual agent, the user can retrieve messages by category, keywords, and date. Thus, the user can find important information whenever necessary, which would relieve the anxiety for the forgetfulness.

B. Deploying Prototype in Actual Households

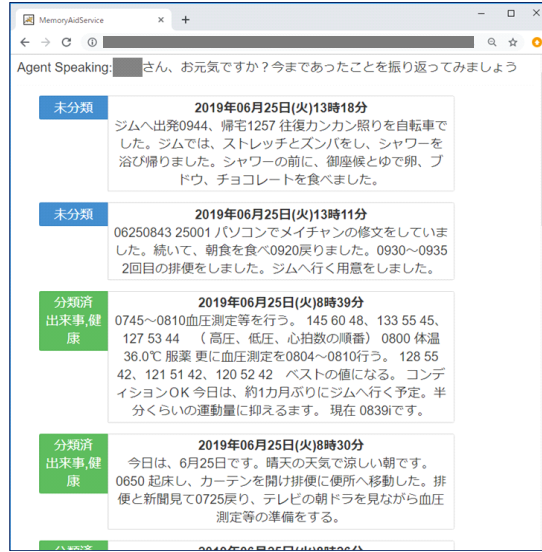
We have implemented a prototype of the memory-aid service as a Web application operated on both a smartphone and PC. In particular, we implemented the chatbot with the LINE Messaging API [12]. To manage the data obtained by the mind sensing, we deployed MongoDB. For inserting and retrieving data via the Internet, we implemented REST Web-API using the Jersey RESTful Web Services framework.

Figure 2(a) shows a screenshot of the Chatbot-based Mind Sensing, where the LINE chatbot asked the user what happened in the Japanese room, and the user answers his activities. Figure 2(b) shows the screen of the short-term retrospective process, where the user corrects and classifies the latest messages. Figure 2(c) shows the screen of the long-term retrospective process, where the user searches messages with the "health" category.

To evaluate the practical feasibility, the prototype system has been deployed and operated within actual households. Especially, Subject A (a 77-year-old man) and Subject B (70-year-old man) are actively cooperating on our experiment. The current rules of the mind sensing are as follows. When the



(a) Chatbot-based Mind Sensing



(b) Short-term Retrospective



(c) Long-term Retrospective

Fig. 2. Screenshots of the memory-aid service

activity recognition system detects the wake up of the subject, the chatbot on the mobile phone asks the physical condition of the subject. When the system detects any activity, the chatbot asks a question depending on the context. At the end of the day, the chatbot encourages to perform the retrospective process.

To respond to the chatbot, Subject A manually inputs the text on the LINE application, whereas Subject B is using the speech-to-text feature of the mobile phone. The subjects sometimes talk to the chatbot just for the recording purpose, even when there is no question.

III. RECORDING HEALTH STATUS WITH MIND SENSING

A. Motivating Example

In the experiment in Section II-B, we found that the subjects talked to the chatbot about various topics. In particular, these healthy elders spontaneously recorded health-related data. For example, let us translate the third message in Figure 2(b).

— 2019-06-25 (Tue) 8:39 —

During 7:45 and 8:34, I measured blood pressure. The values were 145 60 48, ... (top, bottom, heart rate, respectively). At 8:00, body temperature was 36.0 Celsius. I took the medicine... The condition is OK. Today, I will go to the training gym after one month absence. ...

Applying a simple text mining to this message can retrieve important health metrics helpful to in-home self-care. Of course, these subjects were considerably motivated for their health. However, we believe that recording the health data within the mind sensing is possible for general elderly people, with a solid framework and appropriate intervention. In this paper, we investigate a method that exploits the chatbot-based mind sensing for the purpose of recording health status.

B. Declaring Metrics to Record

There are various kinds of data characterizing one's health status, and the data of interest varies among individuals. One may be interested in weight, while another may be interested in blood pressure. To make the framework flexible and sustainable, the proposed method first requires every user to *declare* metrics that he/she wants to record within the system. When a user declares a metric, the proposed method asks the user to define the following attributes:

- **Name:** defines the identifier of the metric (e.g., weight, condition, blood pressure).
- **Type:** defines the type of the value of the metric by *numeric*, *enumerate*, *structured*, or *time*.
- **Unit:** defines the unit of the metric (e.g., kg, None, mmHg).
- **Reporting Time:** defines the ideal time for the user to report the measurement.

Let us see the previous example. If the user wishes to record the body temperature, condition, and blood pressure, the user submits the following three declarations to the system:

```
d1 = {name:"body temperature",
      type:numeric, unit:"Celcius",
      rep_time:08:00:00}
d2 = {name:"condition", type:enumerate
      {"OK":1, "NG":0}, unit:None,
      rep_time:08:00:00}
d3 = {name:"blood pressure", type:
      structured {"top":{"type:numeric,
                        unit:"mmHg"}, "bottom":{"type:
                        numeric, unit:"mmHg"},
      rep_time:08:00:00}
```

Declaration d1 defines the body temperature, where it takes a numeric value, the unit is Celsius, and the user wishes to record around 8 o'clock. Next, d2 defines the condition by enumerate type of "OK" or "NG" (No Good) whose values are encoded by 1 or 0, respectively. Finally, d3 defines the blood pressure by structured data, consisting of "top" and "bottom" both of which take numeric values with the unit of "mmHg".

C. Recording Health Status with Chatbot

Once health metrics are declared by a user, the system encourages the user to record the values. For each declared metric, when the reporting time comes, the system commands the chatbot to ask the user the value of the metric. For example, for the declarations of d1, d2, d3, the chatbot "Mei-chan" talks to the user at eight o'clock every day, like:

Mei-chan: Good morning, Mr. Maeda!
How are you? Please report your
- body temperature
- condition (OK or NG)
- blood pressure (top and bottom)
to me. Have a wonderful day!

On receiving the message from the chatbot, the user measures the values using measuring instruments of own, and sends the answer to the chatbot. For this, the user can talk by his/her own words, but the name of each metric should precede its value, without interleaving other metrics.

Maeda: Good morning, Mei-chan.
My body temperature is 35.7. Blood
pressure measurements were 135 and 88.
Condition is OK. Thank you!

The answer message to the chatbot is then recorded in the database with a timestamp. Of course, the user could make typos and errors in the message, especially when using the speech-to-text input on the mobile phone. Once the message is sent, these errors cannot be corrected on the mobile phone. Instead, the user can use the Memory-Aid Retrospective (see Section II-A) to correct the errors and proof-read the message again. This is also good for the user to reflect the health status.

For sustainable recording, we consider that the system should not force the user to be punctual. Even if the values are not measured at the reporting time, the message from the chatbot would stimulate the user to record them later. Our current aim is *once-daily recording* of health status.

D. Extracting Metrics Values from Messages

Applying data mining to the recorded messages in the database, we extract values of metrics. Here, we suppose that each message follows the convention that "the name of each metric should precede its value without interleaving other metrics". Then, the following algorithm derives time-series values $M(u, t)$ of a metric M of a user u at time t .

Data-Mining Algorithm:

Input: declaration of metric M , user u

Output: time-series values $M(u, t)$ of M of u at time t

Procedure:

- 1) From all messages sent by u , find messages containing $M.name$ as words. Let S_M be the set of the found messages.
- 2) For each message $m \in S_M$, search each word after $M.name$, and find a value v that conforms to $M.type$. Let t be the timestamp of m . Output v as $M(u, t)$.

Suppose that Mr. Maeda sent the message in Section III-C on 2019-06-27 (Thr) 08:15:33. Then, the algorithm derives

```
body_temperature(maeda, t)=35.7
blood_pressure(maeda, t)={135, 88}
condition(maeda, t)= OK
```

where $t = 2019-06-27T08:15:33$.

The step 1) of the procedure can be performed by a search query of the database. The step 2) can be implemented by *text pattern matching* with regular expressions.

E. Visualizing Time-Series Data

Finally, the time-series values of each metric are plotted in a graph, with which the user can review the history of the health status. According to the basis of the once-daily recording, we *downsample* the time-series values to daily frequency, discarding the time of the day. If the resolution of daily frequency is too fine, we can downsample the data to weekly frequency, with appropriate aggregation.

The downsampled time-series data of $M(u, t)$ is then plotted on a graph, where the horizontal axis represents t and the vertical axis plots the value of $M(u, t)$.

IV. PRELIMINARY EXPERIMENT

A. Assumption and Health Metrics

To see the practical feasibility, we conduct an experiment that visualizes daily health status from messages recorded by the mind sensing. In fact, the integration of the proposed method into the memory-aid service is yet under implementation. Therefore, in this preliminary study, we analyze the existing data of Subjects A and B (see Section II-B), assuming that they followed the instruction of the proposed method.

Investigating the existing data, we found that each subject regularly recorded the following metrics:

Subject A (based on data since 2019-03-28 till 2019-06-27):

- blood pressure (top, bottom, and heart rate)
- the number of steps in daily walking
- condition (OK or NG)
- calory consumption in walking and the training gym

Subject B (based on data since 2018-12-18 till 2019-06-27):

- blood pressure (top, bottom, and heart rate)
- weight
- hours of sleep and get up

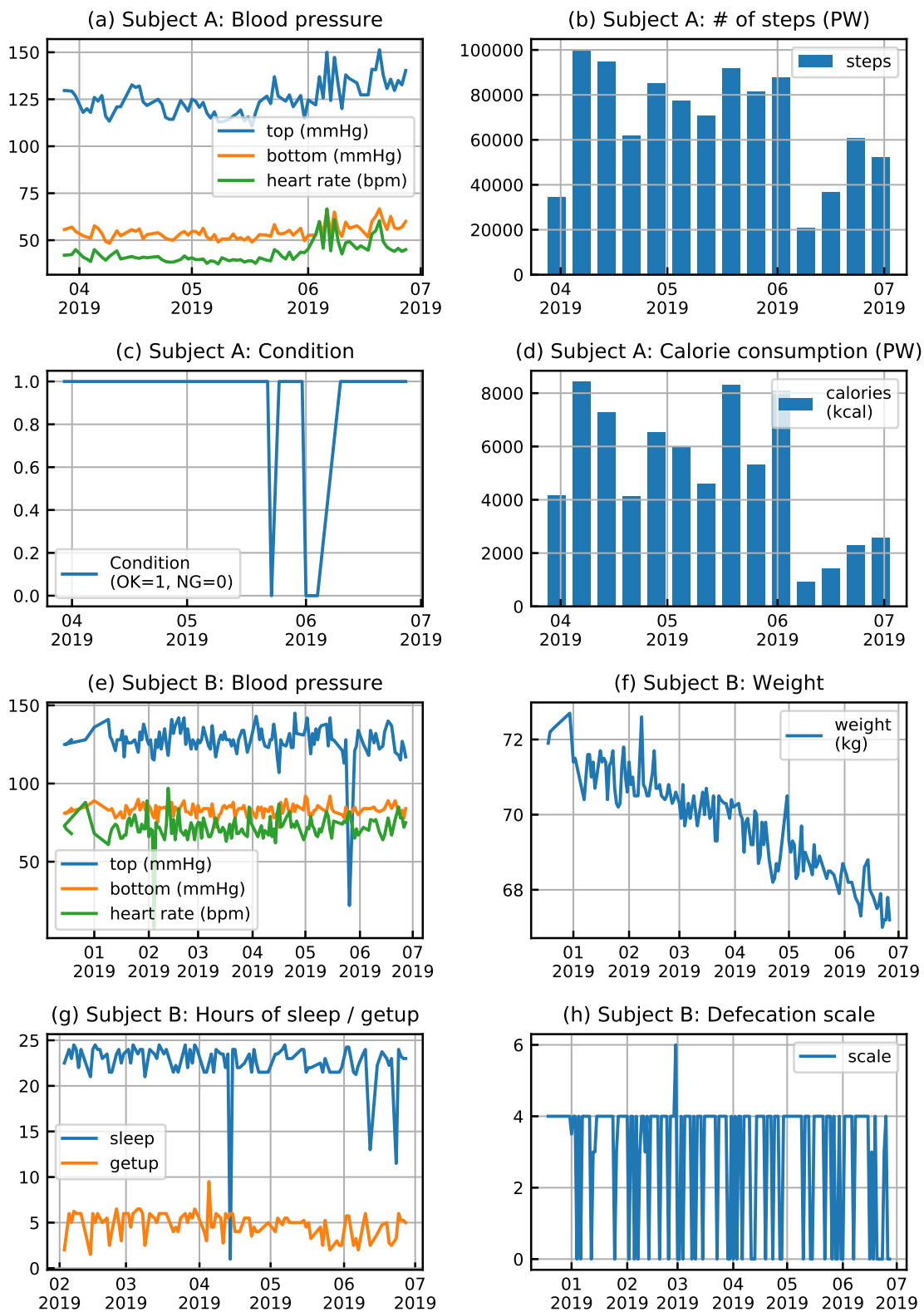


Fig. 3. Visualization of health metrics of Subjects A and B recorded in the memory-aid service

- defecation scale (Bristol stool form scale [13])

For each metric, we specified the declaration. Then, we applied the proposed data-mining algorithm and the visualization to the recorded data of the memory-aid service.

B. Results

Figure 3 shows graphs that visualize the individual metrics of the subjects. As for graphs (b) and (d), the time-series values have been aggregated per-week (PW) by total, since the daily frequency was too fine to visualize. From the graphs, we can clearly observe changes in their health status.

First, let us see the health status of Subject A. In graph (a), we can observe sharp fluctuations in blood pressure and heart rate around the beginning of June 2019. Accordingly, the condition dropped to no-good shown in graph (c). Recently, we interviewed Subject A what happened, and he told us that he suffered from mild bacterial pneumonia during that period. Fortunately, he has completely recovered from the disease now. After the recovery, we slowly restarted the daily exercise. However, he is intentionally reducing the amount of the exercise, as we can see the number of steps and the calorie consumption in graphs (b) and (d).

Next, let us see the result of Subject B. From graph (e), we can see the blood pressure is stable within acceptable range. The sudden drop of the top value at the end of May 2019 was due to the error of recording, as he mistakenly inputs the value 022 instead of 122. From graph (f), Subject B is losing weight significantly. As we asked, he has been on a diet to reduce the weight to alleviate knee pain. It is recommended by his physical therapist. From graph (g), we can see that Subject B regularly gets up around five o'clock, however, he sometimes goes to bed in unusual hours. From graph (h), the value of the Bristol scale is usually 4 or 3, which is quite normal. However, the scale is not recorded every day as we can see a lot of zero values.

V. DISCUSSION AND CONCLUDING REMARKS

In this paper, we have presented a method that allows a user to record and review the daily health status through conversation with a chatbot on a mobile phone. For each metric declared by the user, the chatbot autonomously asks the current value, and the user answers to record. The time-stamped conversations stored in a database are then put in data mining process to visualize time-series values of the metrics.

We have also conducted a preliminary experiment visualizing health status of two healthy elders from the existing data of our previous study. As shown in the experiment, the proposed method successfully extracted and visualized the health status from the records of mind sensing.

In fact, many elderly people are measuring own health data at home. However, most data is volatile without being recorded, and is not utilized effectively. Recently, "connected" health-care devices appear on the market. However, even without such devices, the chatbot-based mind sensing can be a practical method to record and utilize the health data.

Of course, there are many open issues. Firstly, it is important to consider how to design attractive dialogues of the chatbot, so as to keep the motivation of general elderly people. Also, in addition to the visualization, the system should provide appropriate intervention depending on the health status. Previously, a medical examination by interview was the only way for a doctor to know daily circumstances of elderly people. Sharing the recorded data between the user and his/her family doctor would be a great help for efficient medical treatments. These issues will be addressed in our future work.

ACKNOWLEDGMENT

This research was partially supported by JSPS KAKENHI Grant Numbers JP19H01138, JP17H00731, JP18H03242, JP18H03342, JP19K02973.

REFERENCES

- [1] Government of Japan, "Annual report on the aging society (2018)," <http://www.cao.go.jp/>, June 2018.
- [2] K. Tamamizu, S. Sakakibara, S. Saiki, M. Nakamura, and K. Yasuda, "Machine learning approach to recognizing indoor activities based on detection of environmental change," in *11th World conference of Gerontechnology (ISG2018)*, vol. 17, May 2018, p. 118s, st. Petersburg, USA.
- [3] L. Niu, S. Saiki, and M. Nakamura, "Using non-intrusive environmental sensing for adls recognition in one-person household," *International Journal of Software Innovation (IJSI)*, vol. 6, no. 4, pp. 16–29, August 2018.
- [4] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SigKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74–82, 2011.
- [5] Z. Wang, Z. Yang, and T. Dong, "A review of wearable technologies for elderly care that can accurately track indoor position, recognize physical activities and monitor vital signs in real time," *Sensors*, vol. 17, no. 2, 2017. [Online]. Available: <https://www.mdpi.com/1424-8220/17/2/341>
- [6] K. Ueda, M. Tamai, and K. Yasumoto, "A method for recognizing living activities in homes using positioning sensor and power meters," in *2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, March 2015, pp. 354–359.
- [7] G. Di Cesare, C. Di Dio, M. Marchi, and G. Rizzolatti, "Expressing our internal states and understanding those of others," *Proceedings of the National Academy of Sciences*, vol. 112, no. 33, pp. 10331–10335, 2015.
- [8] M. Nakamura, K. Hatano, J. Miyazaki, K. Yasuda, N. Kuwahara, H. Kazui, S. Saiki, S. Tokunaga, M. Otake, N. Kodama, and N. Kosugi, "Developing a system for self-care and mutual-aids of elderly people at home based on externalization of internal states," *JSPS KAKENHI, Grant-in-Aid for Scientific Research (A)*, no. 19H01138, 2019-2023.
- [9] H. Maeda, S. Saiki, M. Nakamura, and K. Yasuda, "Proposal of memory aid service using mind sensing by virtual agent," in *IEICE Technical Report*, vol. 118, no. 511, SC2018-40, March 2019, pp. 19–24.
- [10] S. Sakakibara, S. Saiki, M. Nakamura, and S. Matsumoto, "Indoor environment sensing service in smart city using autonomous sensor box," in *15th IEEE/ACIS International Conference on Computer and Information Science (ICIS 2016)*, June 2016, pp. 885–890, okayama, Japan.
- [11] S. Nakatani, S. Saiki, M. Nakamura, and K. Yasuda, "Generating personalized virtual agent in speech dialogue system for people with dementia," in *Digital Human Modeling 2018 (DHM 2018), Held as Part of HCI International 2018*, vol. LNCS 10917. Springer, July 2018, pp. 326–337, las Vegas, USA.
- [12] "LINE Messaging API," <https://developers.line.biz/ja/services/messaging-api/>, July 2018.
- [13] S. J. Lewis and K. W. Heaton, "Stool form scale as a useful guide to intestinal transit time," *Scandinavian Journal of Gastroenterology*, vol. 32, no. 9, pp. 920–924, 1997, pMID: 9299672. [Online]. Available: <https://doi.org/10.3109/00365529709011203>