Capturing Activities of Daily Living for Elderly at Home Based on Environment Change and Speech Dialog

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Abstract. The ICT-based elderly monitoring systems attract great attention as a promising technology for home elderly care. However, the conventional systems have limitations of deployment cost and invasiveness, the effort of activity labeling, and a lack of communication. To cope with the limitations, we propose a system that captures activities of daily living (ADL) of the elderly, based on speech dialogue triggered by environment changes. Specifically, we deploy Autonomous Sensor Boxes, developed in our previous study, within a house of the elderly. The boxes gather and send house environmental data to the cloud. Then, the Change Finder algorithm is applied to the time-series data, to detect changes in the house online. On detecting a change, the Virtual Agent (VA) in the house asks the elderly what he/she is doing now. The elderly speaks to the VA, by which an ADL is recorded in the system. The proposed system can capture ADL with non-invasive sensing and create an opportunity for communication.

Keywords: Home elderly care · Changing detection · Activity recognition · Virtual Agent

1 Introduction

Nowadays, Japan has been facing a hyper-aging society. In 2025, the total population will decrease to 120 million, while people over the age of 65 will increase to 37 million. Thus, approximately 30% of the population will become the elderly [2]. On the other hands, many facilities of welfare and nursing care suffer from a chronic shortage of workers. As a result, related jobs opening ratio is as high as 2.68 (as of Dec. 2014). The number of nursing home is not sufficient for the number of applicants, who are over 524,000 elderly people. The Japanese government starts to encourage *home care* rather than building new facilities. Needless to say, the elderly care will rely more on home, which poses a burden to the

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family as caregivers. Under these circumstances, the system and the technology, which reduces burdens of elderly care at home, attract great attention.

Among many technologies which are being used to realize care at home studied so far, the *elderly monitoring system* based on ICT is a promising system. As examples of the elderly monitoring system, commercialized systems which detect leaving the bed [4] and which safeguard elderly's health and well-being using robots [1] are enumerated. Especially these days, many researchers enthusiastically develop the monitoring system which recognizes *activities of daily living (ADL)* using activity recognition technology, and notifies caregivers of elderly's emergency situations. Under activity recognition technology, a lot of data is collected with sensors such as environment sensors, wearable sensors and cameras, and conditions or activities of a target elderly are estimated and recognized. As examples of activity recognition technology based on sensor data, there are technologies that learn and recognize the presence and ADL [3] using camera images, and learn acceleration data collected with wearable sensors or smartphone and recognize user's actions (e.g. walking, working, at rest) [6], and recognize ADL using many environment sensors which are installed widely in a smart home [10].

However, the conventional monitoring systems have following problems.

Problem P1 (installation cost and invasiveness). When users install the conventional system to general households, they have to do repair work on their house. As a result, this causes a significant cost to increase. For example, users have to upgrade and install sensors in the house to turn into a smart home. Also, the conventional systems using cameras and/or wearable sensors are very invasive for the daily life of elderly.

Problem P2 (burden of labeling data with activity of elderly). Most of conventional systems classify sensor data into each ADL using machine learning. In order to classify the data, the conventional systems need ADL labeled training data. Therefore, on the conventional systems, users must record and input ADL every several minutes. Thus, this is a heavy burden to elderly and caregivers.

Problem P3 (lack of communication with elderly). Almost all of the conventional systems only notify caregivers when an emergency occurs. Most of the conventional systems can not care with communication, which is essentially important in elderly care. Therefore significant burden cutdown of caregivers is not be achieved.

To cope with these problems, in this paper, we propose new sensing system to capture the ADL of elderly based on dialog triggered by environment changes in a home.

First, for P1, we use an autonomous sensor box [7] in a home which our research group has developed in the previous work. The sensor box is an IoT device which consists of seven environment sensors, temperature sensor, humidity sensor, light sensor, atmosphere pressure sensor, sound sensor, vibration sensor, and motion sensor. The sensor box autonomously monitors surrounding environment by only powering up the sensor box and uploads sensor data to a database on the cloud. Also, we can install the sensor box in various places easily. Furthermore, the sensor box is a non-invasive device for elderly because the sensor box monitors the only environment.

Second, for P2, we propose the ADL labeling method based on changing point detection. We use time-series analysis for monitored environment data and we let elderly input ADL only when the environment changes. In this study, we use *Change Finder algorithm* [8] for environment time-series data collected on the cloud and implement the service which detects changing points online.

Finally, for P3, we use speech dialog with a *Virtual Agent (VA)* [5] in order to input ADL by elderly. When Change Finder detects environment changes, the VA in a home asks elderly what he/she is doing now. Then the elderly answering the question with voice, the proposed system records his/her ADL.

Using the proposed system, we can record ADL without too much burden with non-invasive sensing and the proposed system can encourage communication with elderly using dialogue and concern. Thus installing the proposed system is easier than installing conventional systems and the proposed system can provide care, which is more supportive for elderly.

2 Preliminaries

2.1 Home Care for Elderly

Home care workers always perform following three processes.

Observation: This is to monitor the environment and the behavior of elderly. They continuously observe situations in a home such as time, sound, vibration and a place of elderly. And recognizing situations such as what elderly is doing now and if elderly's body is not in any danger, they take precautions for possible danger and care. For example, they observe that "elderly watches TV and laughs" and "elderly almost falls over while walking".

Care: This is to care actually for elderly based on dialogue. Dialogue means that care workers call elderly's name or nickname and talk to elderly slowly, shortly and simply. Based on dialogue, care workers can let elderly talk about their feeling, and check elderly's condition and ease elderly's anxiousness and loneliness. Also, care workers consider and provide appropriate care depending on elderly's activity recognized by dialogue and observation. For example, care workers talk about TV program when elderly watch the TV program and laugh. In the case that elderly almost fall over while walking, care workers support elderly walking and ask his/her condition.

Record: This is to record care provided actually and what happens in the day. Based on records, care workers report to elderly's family on what has happened and what kinds of care they have provided. Also, keeping recording, care workers recognize features of elderly such as interest, and make use of records for better care for elderly. Furthermore, using records, new home workers turn over appropriate care for the elderly easily when home workers switch shifts with new home workers.

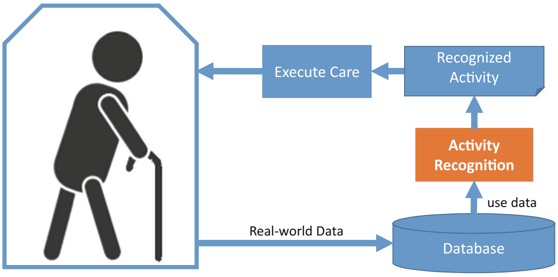

Fig. 1. Common process of monitoring elderly in home based on ICT

2.2 Monitoring Elderly and Recognizing Activities Based on ICT

Figure 1 shows the common process of monitoring elderly in a home based on ICT. In this process, first, systems monitor actual world data and recognize conditions of elderly and the environment around them. Monitored data include biological data (e.g. beat, acceleration of arms, legs, body) and environment data (e.g. temperature, humidity, sound volume, light, motion). Second, on recognition process, systems recognize *activities of daily living (ADL)* of elderly using monitored data. Finally, systems select needed care and provide care actually based on recognized ADL. Supporting parts of observation, care, and record based on ICT, systems ease burdens of home care workers and aim at the improvement of care that the only human provides.

Recently, many researchers enthusiastically study methods estimating ADL of human based on ICT. These methods are expected to be applied to a process of activity recognition, which Fig. 1 shows. These methods try to automatically estimate and recognize activities or postures of users using diverse data monitored by various sensors such as environment sensors, wearable sensors, and cameras. In general, these methods base on machine learning and return labels of concrete ADL based on given row data (time-series data) by *learning without a teacher* or *supervised learning*. In supervised learning, users label data, which are monitored by various sensors, with actual ADL previously to make training data. And picking out feature quantity of training data, systems learn by machine learning methods such as Support Vector Machine (SVM). In learning without a teacher, systems analyze a cluster of given data and perform mapping each cluster to each ADL.

As described in Sect. 1, many methods for activity recognition have been proposed before such as methods using camera images [3], using smartphone [6], and, using indoor positioning with smart home and power consumption [10].

2.3 Problem of Conventional Monitoring Systems

In this paper, we focus on Problem P1, P2, P3 described in Sect. 1 as problems which conventional monitoring systems have.

– *Problem P1 (installation cost and invasiveness)*
– *Problem P2 (burden of labeling data with activity of elderly)*
– *Problem P3 (lack of communication with elderly)*

Problem P1 has roots in that latest activity recognition technologies are still too unreachable for monitoring elderly at general households to use. More non-invasive and lower cost systems are needed to become widely used. Problem P2 means taking a lot of trouble with making training data for machine learning soon after installing systems. Reusing training data collected in other environments is difficult because conditions and living environments of elderly are different for every elderly. Problem P3 has roots in that almost all of conventional systems depend on the care of caregivers. Thoughtful common communication with elderly, who are monitored actually, is needed unless elderly is in an emergency.

2.4 Previous Works

In the previous work [7], we have developed *autonomous sensor boxes* which consist of a small box containing several sensors connected with a single board computer. The sensor box is an IoT device which has seven environment sensors, temperature sensor, humidity sensor, light sensor, atmosphere pressure sensor, sound sensor, vibration sensor and motion sensor. All you have to do is powering up the sensor box and the sensor box monitors autonomously environment. Also, the sensor box uploads monitored data to a database on the cloud. We can access the data collected on the cloud using Web-API. Also, external applications can get arbitrary time-series data using platform-independent Web protocol (REST or SOAP). We can install sensor boxes at anywhere easily and sensor boxes monitor the environment. Thus the sensor box is non-invasive for user's daily living. Therefore the sensor box can be used as the technology supporting to observe and record in home elderly care.

Also, in the previous work [9], we study to use *Virtual Agent (VA)* for supporting communication with elderly. VA is a chat bot program which looks like human and has animation effects and can interact with voice. Elderly can communicate with VA in the display. Therefore VA can be used as voice interface to provide care and dialogue on home care.

3 Proposed ADL Sensing System

To cope with problems P1, P2, P3 described in Sect. 2.3, in this study, we propose new sensing system capturing the ADL of elderly based on dialog triggered by environment change in a home.

3.1 Key Idea

In the proposed system, we install autonomous sensor boxes (refer to Sect. 2.4) in elderly's home and the proposed system monitors environment. This achieves non-invasive and lower cost sensing and we set out to solve Problem P1. Next, the

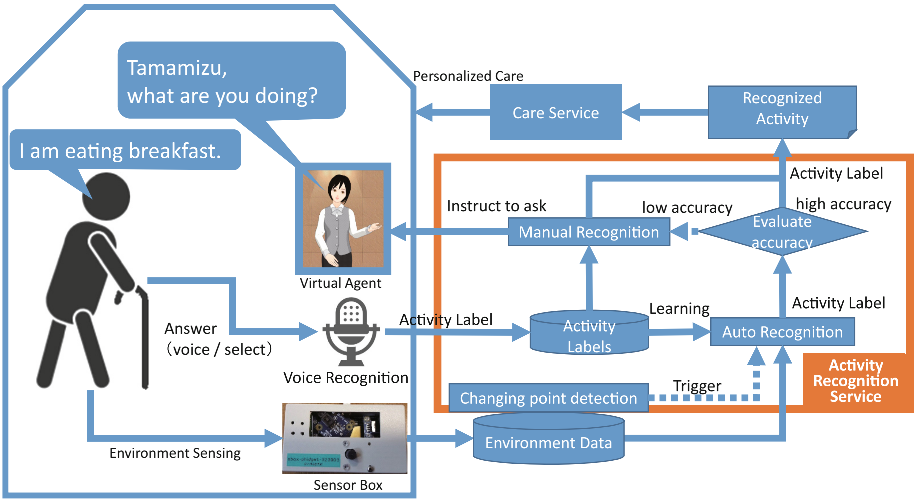

Fig. 2. System architecture of the proposed system

proposed system analyzes data collected by environment sensing and performs *changing point detection* online. Changing point detection identifies changes of data behavior. Using changing point detection, the proposed system estimates environment changing point as activity changing point. And recording elderly's ADL only on the timing of detection, the proposed system eases burdens of labeling described in Problem P2. Furthermore, the proposed system uses communication and dialogue with VA when the proposed system inputs ADL. When environment in the home changes, VA asks elderly what he/she is doing now (we call this *speech dialog*). The elderly answers the question of speech dialog with voice and the system record his/her ADL. This process encourages communication and leads to solving Problem P3.

In the proposed system, it is expected to become less recognition accuracy than conventional activity recognition methods because the proposed system only uses non-invasive environment sensing. However, the proposed system cover all activity recognition by not only sensing but also hearing ADL from elderly directly through communication between elderly and VA. And this creates communication chance and aims to achieve to record ADL with a high degree of accuracy.

3.2 System Architecture

Figure 2 shows the system architecture of the proposed system. The architecture consists of sensing environment, Activity Recognition Service, and Care Service. We present summaries of each part's performance below.

Environment Sensing: We install autonomous sensor boxes in elderly's house and the proposed system monitors the environment. The system gets environment data, temperature, humidity, light, atmosphere pressure, sound volume, vibration, and motion, and these data is uploaded to a database on the cloud with date and time.

Activity Recognition Service: The system periodically detects changing point online each time when the environment data is uploaded. When the system detects changes of environment, this triggers that the system executes *auto activity recognition*. In auto activity recognition, the system outputs estimated activity labels and accuracy. In the case of high accuracy, this service sends the activity label to Care Service. In the case of low accuracy, the system executes *manual activity recognition*. In manual activity recognition, VA greets elderly and asks elderly what he/she is doing now. And elderly answers ADL with voice or touching display. Then the service gets activity label and sends this to Care Service. Also, the proposed service uses this activity label as training data for auto activity recognition.

Care Service: This service selects and executes suitable care based on activity labels received from activity recognition service. This service issues an instruction to VA and lets VA communicate with elderly. Also, in the case of emergency, this service notifies caregivers.

Specifically, in this paper, we focus on changing point detection and manual activity recognition in activity recognition service.

3.3 Changing Point Detection Using Change Finder

Changing point detection is the technology detecting changing point of time-series data. This falls into two categories, *offline detection* and *online detection*. Offline detection uses a batch process for data have been collected and find changing points. On the other hands, online detection judge if the data is changing point in each time when new data is presented. In the proposed system, we use online detection to judge environment changes quickly on monitoring elderly. Specifically, in this paper, we implement *Change Finder* [8], which is one of online changing point detection methods.

Change Finder is characterized by autoregression model (AR model) and two phases learning using smoothing. Change Finder has a mechanism for detecting changes of time-series model and calculates the degree of changes as the changing score. Changing score is high when the degree of changes is high. Also, changing score is low when the degree of changes is low. Change Finder has two AR models. The first model learns original time-series data. The second model learns the degree of changes, which is calculated based on the first model as time-series data. This leads to remove changes raised by small noises. Also, using SDAR (Sequentially Discounting AR model learning) algorithm, Change Finder achieves processing speed as fast as Change Finder can process online. Also, whereas AR model requires stationarity of data, Change Finder can manipulate non-stationary data.

Change Finder in the proposed system processes for time-series data collected by environment sensing as following:

Step 1: Change Finder receives a collected environment data as input and learns the first AR model. In this step, Change Finder updates average, variance, covariance and autoregression coefficients, which AR model has. The equations of the update are given as following.

$$\mu_t = (1-r)\mu_{t-1} + rx_t \tag{1}$$

$$C_{t,i} = (1-r)C_{t-1,i} + r(x_t - \mu_t)(x_{t-i} - \mu_t)(i = 0, ..., k) \tag{2}$$

$$C_{t,i} = \sum_{j=1}^{k} a_{t,j} C_{t,i-j} (i = 1, ..., k) \tag{3}$$

$$\hat{x}_t = \sum_{i=1}^{k} a_{t,i}(x_{t-i} - \mu_t) + \mu_t \tag{4}$$

$$\sigma_t = (1-r)\sigma_{t-1} + r(x_t - \hat{x}_t)(x_t - \hat{x}_t) \tag{5}$$

Here, the step is t, autoregression order is k, input data is x_t, the average is μ_t, autoregression coefficients is $a_{t,i}$, covariance is $C_{t,i}$, the variance is σ_t and forgetting rate is r. Expression (3) is solved by applying the Yule-Walker method and we obtain $a_{t,j}$. In this regard, $C_{t,-i}$ equals $C_{t,i}$.

Step 2: In this step, Change Finder calculates scores using normal probability density distribution based on average and variance that results from Step 1. The equation of calculating score is given as following.

$$y_t = -\log_{10} p_t(x_t) \tag{6}$$

Here, probability density distribution is $p_t(x_t)$ and score is y_t.

Step 3: In this step, Change Finder smoothes scores that result from Step 2 to remove noises. The equation of smoothing is given as following.

$$Score_t = \frac{\sum_{i=0}^{w-1} y_{t-i}}{w} \tag{7}$$

Here, the width of smoothing is w and a result of smoothing is $score_t$.

Step 4: Using $Score_t$ that results from Step 3 as new time-series data, Change Finder performs the second round of learning, calculating score and smoothing just like Step 1–Step 3. And we obtain scores that result from the second round of Step 3 as the changing score. Also, Change Finder judges scores over given threshold as changing points.

3.4 Manual Activity Recognition

In manual activity recognition, using VA, the proposed system asks elderly activities and recognizes ADL from elderly's answer. The system changes the speech into the text using speech recognition. If there were keywords in the answer, that is changed by speech to text, the system would label with ADL. For example, in the case that the answer includes "brekky", the system labels with "breakfast" and inserts to the database. In particular, the system labels with ADL as the following step.

Step 1 (Asking for elderly's ADL): When Change Finder detects changes of environment, VA asks elderly that "Hi, ___. What are you doing now?".

Step 2 (Speech recognition of answer): Elderly answers with a voice for a question from VA. Then the system handles voice recognition for an answer from starting to speak to finishing. And the system changes the voice into the text.

Step 3 (Checking keywords): Users register keywords related to ADL in advance. Next, the system checks if the text, that results from Step 2, includes keywords. When the text includes keywords, the system performs Step 4. On the other hands, when the text does not include keywords, the system performs Step 1 and asks again.

Step 4 (Executing actions): The system executes actions appropriate to a keyword, which is matched in Step 3. The system has functions (e.g. label with ADL, answer using VA and answer using pictures or movies) as actions. In the function labeling with ADL, the system labels with ADL related to keywords and inserts to the database. In the function answering using pictures or movies, the system uses a mechanism which is developed in [9]. Binding keywords and actions is defined in the system as following.

$$[W : w, A : a_1, a_2, a_3, ..., a_n] \tag{8}$$

Here, W is a keyword and A is actions. Also, w is an actual value of a keyword and $a_1, a_2, ..., a_n$ are executed actions. In the case that an answered text matches a keyword in Step 3, the system executes defined actions in sequence, which are $a_1, a_2, ..., a_n$. For example, we use the rule as following to label with "breakfast" and let VA reply that "Do not forget taking medicine".
[*W:"brekky", A: registerLabel*("*breakfast*"),
talk("*Do not forget taking medicine*")]

4 Implementation

4.1 Prototype System

We implemented prototype system that consists of changing point detection, manual activity recognition and labeling with ADL. Technologies used for the implementation are summarized as follows:

– Development language: Java 1.8.0_25, Ruby 2.1.5
– Database: MongoDB
– Web server: Apache Tomcat 7.0.69
– Web service framework: Jersey 1.19, Axis2 1.6.3

Both services are deployed as Web services. Therefore, these services can be consumed with the platform-independent REST protocol. In this prototype system, we implemented changing point detection and labeling with ADL using Java. And changing point detections for seven time-series data, which are collected with sensor boxes, are performed in parallel using thread. Also, we implemented manual activity recognition with Ruby. Changing point detection, labeling with ADL and interaction with VA worked together using call web services with REST protocol.

Furthermore, we implemented GUI to manage changing point detection and labeling with ADL using technologies as follows:

- Development language: HTML, javascript
- javascript library: jQuery 2.1.4
- CSS framework: Twitter Bootstrap 3.1.1

GUI of changing point detection allows users to register a target sensor, a method of changing point detection freely and parameters for detection. Also, GUI visualizes data collected with a target sensor and changing score calculated with changing point detection as a line chart. GUI of labeling with ADL allows users to check, modify and delete actual labeled ADL. Also, this GUI allows users to input ADL label directly without executing manual activity recognition.

4.2 Case Study

As a practical case study, we have set a sensor box in author's room and have conducted the experiment that the system collects environment data. Next, we have used changing point detection for time-series data of light sensor and have visualized actual changing score. Parameters of Change Finder are the first AR model's degree of 50, the first AR model's forgetting rate of 0.05% and the first smoothing width of 5. Also, parameters of Change Finder are the second AR model's degree of 50, the second AR model's forgetting rate of 0.1% and the second smoothing width of 5. Figure 3 shows actual light sensor data and this changing score on Oct. 23, 2016. The left vertical axis shows changing score and right vertical axis shows light sensor value. According to Fig. 3, it can be seen that score becomes high on points where light changes a lot. Therefore, we have confirmed that changing point detection worked as expected.

Also, we have conducted the experiment that the prototype system labels with "breakfast" when elderly answers including a keyword that is "brekky" as the scenario of manual activity recognition. In this experiment, we have set "awake", "sleep", "take a bath", "out of the bath", "go out", "come home" and "brekky" as keywords. Also, we have defined actions for each keyword, which VA answers "You do ___, don't you?" and labels with corresponding ADL. And we have executed manual activity recognition and have confirmed that "breakfast" label is recorded when the subject answers that I am eating brekky.

4.3 Discussion

According to the diary which the subject records ADL during the experiment, the subject slept at 0;52, woke up at 9:50, took a bath at 11:40, went out at 13:17, came home at 13:30, went out at 19:02 and came home at 22:27. As shown in Fig. 3, each change of activities excluding "went out of 13:17" and "came home

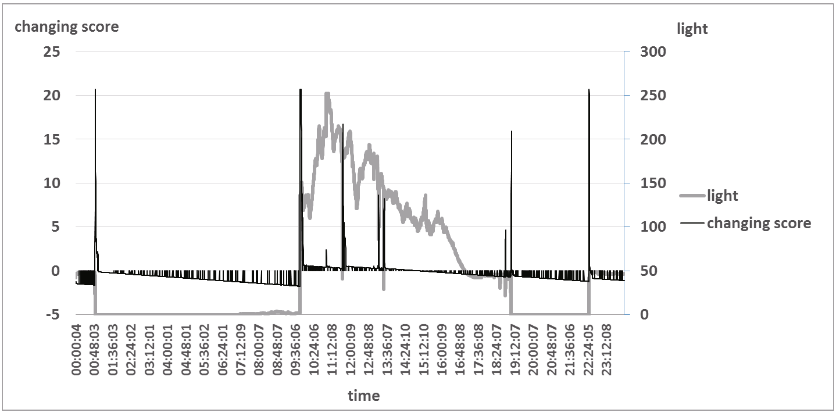

Fig. 3. Light data and changing score on Oct. 23, 2016

at 13:30" are most obvious on changing score. Therefore, the prototype system could estimate parts of timing when ADL changes. As a reason that prototype system can not detect "went out at 13:17" and "came home at 13:30", it is considered that switching light does not contribute illumination intensity of the room because the light sensor is affected by outside light from windows. Also, as a reason that the system can detect other activities, it is considered that opening and closing curtains and switching light of the room contributes illumination intensity and changes of activities are recognized.

On manual activity recognition, we confirmed that the system can record ADL accurately as long as the reply matches keywords prepared in this experiment. However, there are many synonyms such as breakfast and brekky. Thus the system needs to cope with various expressions. We considered that we allow users to register several keywords in the same rule, and to extract keywords which are independent of various expressions and so on to cope with this. Also, in the case of that the system has keywords sounded similar, the probability of false recognition get higher. Therefore we need to adjust rules and try not to register keywords sounded similar one in other rules.

5 Conclusions

In this paper, we proposed new sensing system in order to capture ADL of home elderly. In the proposed system, when the environment around elderly changes, VA talks to elderly. And the proposed system records ADL based on communicating between elderly and VA. This achieves to record ADL with non-invasive environment sensing and promotes communication of elderly. Also, we implemented prototype system. Using the system and changing point detection for light data of author's room, we conducted an experiment in labeling sensor data with ADL. And we preliminarily evaluated the availability of the proposed system.

In our future works, implementing algorithm adjusting threshold which uses to determine changing point, we improve the accuracy of changing point detection. Also, using machine learning (e.g. clustering) for labeled sensor data, we implement the service that automatically recognizes ADL. Furthermore, we let elderly install and use the proposed system to actual elderly home and evaluate the accuracy of changing point detection and activity recognition and evaluate the availability of the system. Finally, we also implement the service which allows users to register suitable cares for recognized ADL and this service promotes to care more supportive for elderly.

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