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The nursing care activity and records estimation using experiment and dataset system

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Abstract - Here, we describe an activity-recognition system that captures the varied activities of elderly individuals in a Japanese nursing home. For the duration of four months, nurses kept track of patients' activity levels, as well as sensor data from their cell phones. Several staff members or nurses have registered 28 different activity labels. The 6-story building's networked system and a mobile app for encoding data make up the system architecture, which serves a large number of people. Even a non-expert nurse or user may easily handle this system because of the system's intuitive design. Using statistical characteristics and an extremely randomized tree, we were able to identify the activities that were taking place. We found inconsistencies in the timestamps at the beginning and end of the recordings. To this end, we investigated the possibility of time reversal. In smart homes or elder care facilities, the information may be used to identify a variety of activities. The dataset is made up of labels that employees put on their phones and care information that they put in the system.

I. Introduction

As our population ages, the need for nursing homes grows, resulting in a labour deficit. The use of information technology to improve nursing care efficiency is critical. Mobile sensors such as cellphones have been used in studies in the area of ubiquitous computing to identify human activities [1]. Nursing care activities, nursing care tasks, and residents' care records may all be recognised using this technology. Using this technology at a nursing home will allow us to better track the care and work of our residents. The nursing facility centre may benefit from this data analysis.

In this study, we used data from a nursing care facility to perform activity recognition. Smartphones are used by nursing staff to keep track of patient care. To increase the effectiveness of nursing care records, we've developed a new system for nursing homes. Phones are used to make nurse care records, and sensor data is sent to a cloud service. We conducted a four-month experiment to gather data from medical records.

During the first two months of employment, employees maintain paper records in addition to electronic ones. In the past two months, they have totally reverted to using the suggested system to store care data. Initially, the system was unfamiliar to the personnel. They got more proficient at keeping track of the passing of time as they became more familiar with the method. Fa

Using the acquired data, we assess whether or not activities may be recognized. Algorithms and measures for assessing class imbalance were utilized. In particular, each class was classified as a one-class subclass. In order to take advantage of user dependence, we expand the label timestamps and perform user-dependent training. As a result of this, five activities had AUCs greater than 80%, and 15 had AUCs greater than 60%.

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Using the information acquired, researchers may use it in care facilities to recognize activity patterns and mine data. Sensor data from employees' cellphones, activity labels, and care information entered into the system are all included in the dataset.

II. Annotation challenge in the wild

There is a lot of literature on activity recognition studies. However, there are few instances of complex tasks being carried out at work locations. Most cases are utilized in health care settings like hospitals and nursing homes.

Data with a training label is required for machine learning algorithms, although this aspect is quite expensive. This is one difficulty. Giving training labels (annotation) in real-time by the person herself/himself is unusual, and if there is a risk that the original responsibility may be altered if s/he conducts extra work, the activity itself becomes weird and strangely performed.

Observers need to be prepared, and manual effort is often required as a result. Even if done later, visualising all of the raw data and assigning a label typically takes longer than the actual duration of the action itself. It is typically more difficult to understand sensor data from acceleration sensors than from video cameras. Video cameras may be set up to take measurements at a specific location or in a lab.

However, in the wild, it might be a challenge to find evidence.

An approach based on a person's memory, and a method to complement and complement experience-based sampling, have been suggested to reduce the strictness necessary for such training labels. Even if the label time is erroneous, we have presented a strategy to increase accuracy.

Using the task records and activity label records often used by nursing staff, we provide in this study a method for integrating them. Even though self-labeling may lead to errors, this method tries to improve the number of labels collected by making recording more convenient.

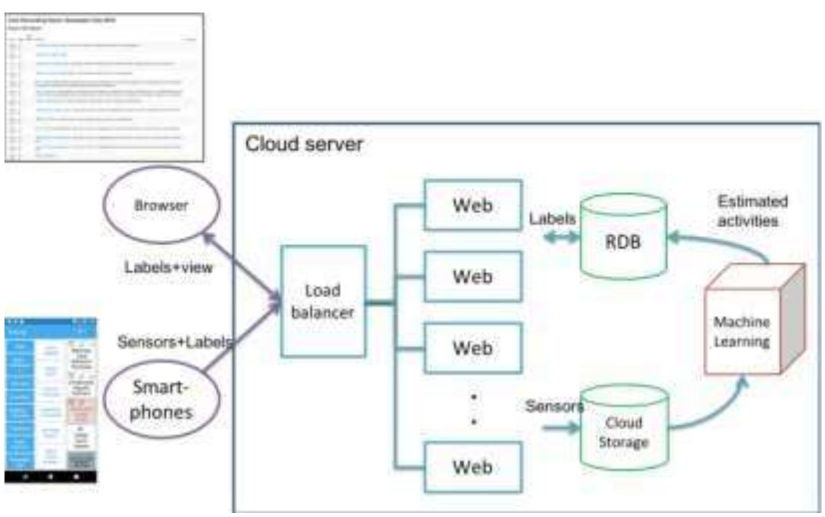

Figure. 1. Care record / activity recognition system configuration.

III. CARE RECORD / ACTIVITY RECOGNITION SYSTEM

It gathers sensors and labels for machine learning, stores them in a cloud server, and lets staff enter nursing care records on their phones while they work at a nursing home. This system's software is an enhancement of [12]. For a few days, activity labels may be used to estimate how much time a nurse spends providing care to patients.

The architecture of this system is presented in Figure 1. Using a Wi-Fi network at the facility, the Smartphone transmits sensor data and nursing care records entered by facility employees to a central server on the cloud side of things. The cloud service offers authentication and Web user interface (UI), and at the same time, it trains the activity recognition model by machine learning from the data received regularly, at the same time identifying activity recognition for sensor data. The predicted activity may be validated and smodified on the Web, which is also, used as learning data for future learning.

A. Smartphone Application

Staff members may submit their care records into the FonLog Android smartphone application while they are working and send it to a cloud server using the smartphone's sensors. It's possible that the nurses you're working with don't even know how to use their phones.

The following features are available with the FonLog smartphone app.

1). It is required to gather the right responses (activity labels) to activities combined with sensor data in order for activity identification to be supervised and machine-learning. Keeping track of the start and finish times of an activity label is essential since it is time-series data. Figure 2 in FonLog demonstrates this.

Figure. 2. Screen for entering care record / activity labels.

"Activity class" indicates what kind of work has to be done, "care target" indicates who needs to be taken care of, and an "activity label" box appears in the right column when the grey button in that column is pressed. To go to before starting (I), just touch an activity label box. Doing something the start and end times of an activity may be recorded using finish (). Like on a slot machine, you may scroll up and down these three columns to see more material than the screen height allows.

The following procedure may be performed as well:

- A lot of different activity labels could start and stop at the same time. This is because one action could be taking place while another is going on.
- Because you may target numerous topics with one activity, like a meal, you can choose multiple subjects for one activity class. "
- The audience might also be categorized by floor or other specific criteria. This may be done on the server-side, and can be retrieved as metadata in the (8) section.
- Section IIIB's Web system uses the HTTPS protocol for user authentication, and after a single login, session information is retained in cookies and files of the programme so that it is possible to log in again automatically.

- The system moves into a background execution state and continues to run as long as data collection continues. The programme may be reopened even if it was suddenly terminated or the terminal was restarted, since it is set using the API given by the OS.

- Every minute, sensor data is sent to the cloud server by means of the HTTPS protocol through buffered data.

- Information on the activity class list, care receivers, and care details input form is needed to retrieve metadata. Every two hours, FonLog pulls these JSON files from the cloud server and shows them on the screen.

B. Nursing care record / activity recognition cloud service

Nursing care records, counting, and activity identification are all handled by the cloud service. It performs the following functions: (1)–(8).

1) A user's email address and password are used to authenticate using a smartphone app like Fon-Log or the UI on the website.

2) Function of receiving activity labels, care information, and sensor data from the smartphone application FonLog using the POST method in HTTPS protocol. CSV files are used to send data, which is then stored in a relational database so that it may be easily accessed. The sensor data are kept in the cloud when the receipt timings have been added.

3) Activity recognition and visualisation function: machine learning is conducted about once per hour and the daily activity of the user is predicted using prior activity labels and sensor data as training data. In the paper [13], we describe a method for recognising a person's daily activities.

4) It is possible to make changes to the activity label and care information entered on a smartphone, as well as the assumed activity from step 3), using the server's Web interface. The next training data is based on the corrected estimated activity.

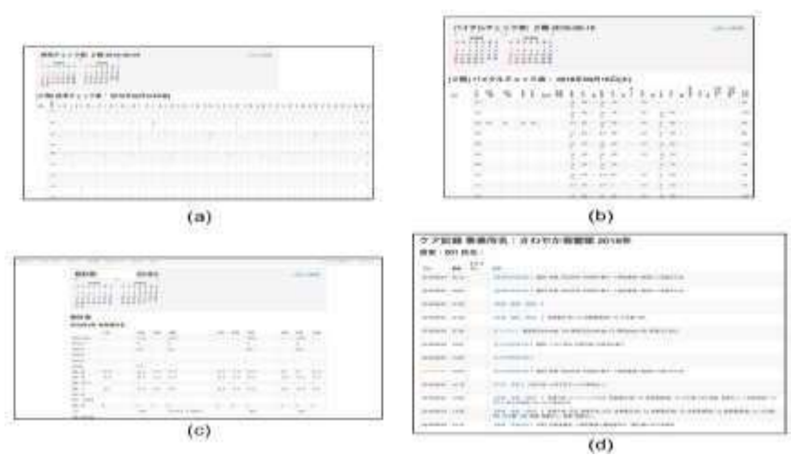

Figure. 3. Database of cloud forms. As demonstrated in Figure 2, activity labels and care information are produced in a nursing home-like format. A care record, as illustrated in Figure (d), is a form to be printed and presented to the municipality.

- As illustrated in Figure 3, the output of activity labels and care information is presented in a manner that is often used in nursing homes. Figure 3 (d) shows an example of a care record, which is a form to be printed and submitted to the municipality at a later time. When there is an emergency, we made buttons for each caregiver to print all of their previous records together so that they can be ready.

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- Additionally, it is feasible to create activity courses that stimulate employees or transmit sentiments of thankfulness through activity labels. This is because the middle row of Figure 2 includes not just the caretaker but also the nursing personnel (a).
- It is possible for the cloud server-side to gather all of the communication between these employees in order to evaluate and improve their work.
- In order to make sure that the data from the smartphone app is being provided appropriately, there is a monitoring mechanism for activity labels, care details, and sensor data. For this reason, our daily checks may be visually checked by counting and showing the number of received data for every caregiver and each cared-for individual.
- Applicable to the smartphone application's function 8, (Metadata download function), is a JSON-based metadata editing function that supports data classes of activity classes, care recipients, and care details.

For implementing the system, Ruby on Rails and Elastic Beanstalk, Amazon's online load balancing PaaS for relational database systems, are the best options for implementing the system. Storage was handled by RDS and S3. When it comes to receiving a huge quantity of sensor data, load balancing is essential, so Elastic Beanstalk's load balancing function is combined with the Web feature. The EC2 server for activity recognition written in R was deployed on EC2, received activity label from RDS, sensor data from S3, and wrote back the estimated result to RDS for the 3rd time.

IV. EXPERIMENT IN A CARE FACILITY

The focus of our experiments in this part is a care facility in Japan, where a large number of elderly individuals are supported by staff and nurses.

In most cases, the target facility's nursing care records are kept by hand. It is important to note that in our experiment, this technique was used alongside the traditional handwritten recording system for the first two months (March and April). In the second part of May and the first half of June, this system's stability and usability greatly improved. Because of this, nurses and other staff members have been instructed to cease maintaining handwritten notes, and all data has been gathered and entered using our system since then. In this way, the system is tested in a real-world setting in a trustworthy way. As a result, our system's resilience is guaranteed in a real-life setting like a nursing home.

We're now going to talk about the actual location where the data is being stored.

The parking lot and entrance are on the ground level, while the administrative offices are on the second floor of a six-story structure. The aged (who we refer to as "residents") are housed in 65 separate rooms on the second through fifth levels. A few common areas may be found on the 2nd and 4th floors, such as the dining room and dining halls; the trash disposal room; the laundry room; and the community restrooms. Experiments involving 27 people, including 23 carers and four nurses, were carried out over the course of four months. During the experiment, which was done by the researchers, workers could keep their phones with them at work and in other places, like their pockets.

A. Experimental Equipment

Plus One Marketing provided us with Priori 3 LTE cellphones for testing.

Mobile data routers and Wi-Fi base station routers were put up on each level since the building lacked network infrastructure like a wireless LAN. Sensor data is saved on the smartphone even if it is not connected to the network, so data is not lost during this process and the network status is realistic. This is even though there was already a mobile router in the area. A special wireless router was built beneath it to make more connections with the smartphone and improve the bandwidth in that area.

B. Activity Classes

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After consulting with the personnel and reviewing manuals such as care records from nursing homes, we came up with a list of 28 different types of activities. Many different types of activities may be found in this dataset. Each activity class has its own set of care details. Table 1 shows the whole list. Among the categories of direct care activities listed in the table are vitals (checking), excretion, and bathing/wiping, maintenance (preparation and checking of goods), medication organisation (organisation of medications), and communication (family/guest response, delegation/meeting) and correspondence with doctors. Several sorts of care details are available, including numerical ones like food intake and drink intake, as well as single-choice options like the location of care support on the body.

TABLE I ACTIVITY CLASSES

1: Vital, 2: Meal / medication, 3: Oral care, 4: Excretion, 5: Bathing / wiping, 6: Treatment, 7: Morning gathering / exercises, 8: Rehabilitation / recreation, 9: Morning care, 10 : Daytime user response, 11: Night care, 12: Nighttime user response, 13: Family / guest response, 14: Outing response, 15: Linen exchange, 16: Cleaning, 17: Handwriting recording, 18: Delegating / meeting, 19: Get up assistance, 20: Change dressing assistance, 21: Washing assistance, 22: Medical doctor visit correspondence, 23: Preparation and inspection of goods, 24: Organization of medications, 25: Family / doctor contact, 26: Break, 27: Emergency response such as accident, and 28: Special remarks / notes

C. Result.

A number of nursing care records and their accompanying recording times were collected and analysed as part of the experiment to determine the impact of the system. Our research focused on —

a) Nursing care records and activity labels are collected by the system or not, and

b) If the system has reduced the time it takes to enter nursing care records.

Two aspects, the quantity of nursing care records and nursing care record time, are discussed here.

1). Number of nursing care records: We gathered 38,076 activity labels, 46,803 record details, and 2834 hours of sensor data throughout this experiment's last two months of usage. Figure 4 depicts the total number of activity labels throughout the course of the four-month period as a time-series graph. Charting time in minutes using an abscissa (time series) and an ordinate (total time in minutes) While in the first half, there were 101 activity labels per day, this number rose to 494.3 labels per day in the second half of the recording period. When comparing this time to the earlier one, the quality of the recordings has improved dramatically.

As for the care record input 1, the care record in Fig. 2 showed whether or not the degree was raised (d). The computer used about 1.5 times the amount of input material.

2). Nursing care record time: The activity record time for Activity Classes was then evaluated. However, when we looked at the recorded activity label's time, we discovered that quite a few tasks were completed in under a minute. Since there were worries that the staff remembered or documented the "time of nursing care record" instead of documenting the "time of activity," we have added extra questions to staff members. As a consequence, in the first half of the studies, 18 participants completed the handwritten records after the activity labels had been completed in the lab. On the other hand, 13 out of 22 participants completed the detailed input once the activity labels were completed over the whole duration. In addition, 11 of the 23 people who filled out the activity labels worked as nurses.

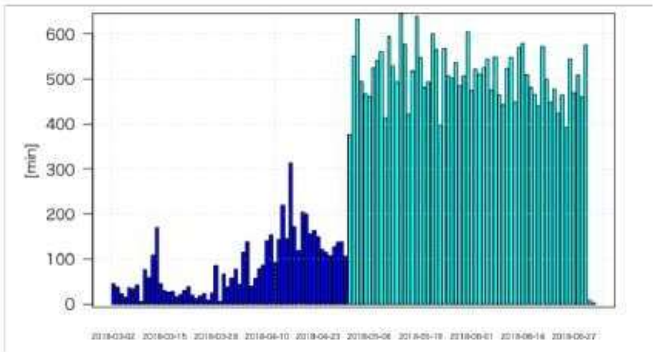

Figure. 4. Daily activity labels during the four months data recordings vs. the total recording period in terms of minutes. In the first half, the average activity labels/day is 101, which has improved to 494.3 during the latter half period of data recordings.

Inaccuracies persist in the start and finish times of activity labels, and the record time can be lowered when compared to the standard handwritten recording method, but label collections can enhance the kinds, number of records, and activity label collections.

We'll look at ways to reduce recording time in the next section, which builds on our work with activity detection.

V. ACTIVITY RECOGNITION FROM SMARTPHONE SENSORS

A machine learning-based solution to recognizing activities was tested. Sensor data has been used to compile this list of activities. Preprocessing and assessment methods using Extremely Randomized Trees are discussed in the following sections.

A. Preprocessing

In this scenario, X, Y, and Z axes data were taken from the accelerometer of the smartphone. Our feature vectors are derived from accelerometer time series data and are based on metrics such as the mean value, standard deviation, maximum and lowest values. For assessment purposes, the activity labels and time stamps were reworked. As previously noted, nearly half of the nurses' records were collected after the activity was completed. Since the primary goal of a nurse is to serve the patient as quickly as possible, this is understandable. Then, the nurse will be able to keep track of the information. Adding records to the system will be more challenging if s/he is overworked. We relocated each activity label to a larger time-segment in order to address this real-world difficulty. We added 20 minutes to the start time and 17 minutes to the end time based on the initially reported timestamps for both the start and the finish. This enhancement has the potential to enhance recognition rates.

B. Evaluation method

The accelerometer data was utilized for statistical analysis. Each user received a set of 1000 features.

The Extremely Randomized Tree [4] is used in our strategy for categorization. A leave-one-day-out cross-validation strategy is used to divide training and testing data.

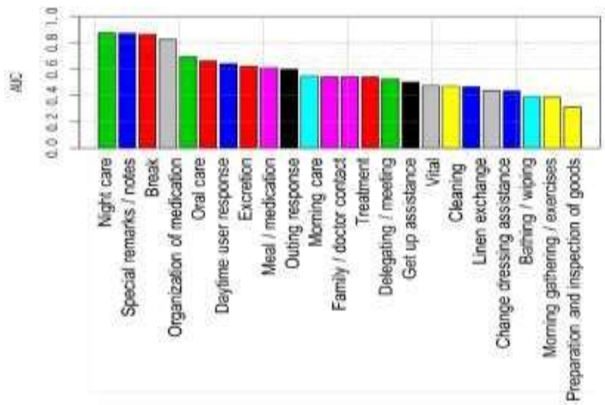

Figure. 5. Reaction time accuracy It demonstrates 80% precision for 4 tasks and 60% accuracy for 10 activities.

C. Discussion

Using a smartphone's accelerometer, for example, it is predicted that this degree of accuracy may be achieved. Nursing care recording systems capture enough samples for each person, which is why there are so many results. Based on these findings, nursing care recording time may be reduced even further. We designed our system's smartphone user interface so that recordings may be made more quickly and intelligently. However, a nurse or caregiver may, in the event of an emergency, enter the data incorrectly. The system's flaws may be uncovered by additional investigation of this dataset. While providing care to an elderly or disabled client, a nurse may need additional time to record the information she collects. Recording time may be shortened with practise and regular use of the system.

VI. CONCLUSION

In this study, we provide a method for nursing staff to record information on patient care, activity labels, and smartphone sensors. At a Japanese elderly home, these statistics were gathered over the course of four months. From the user's perspective, the care record system and its settings have been explained. A smartphone app named FonLog has been created for a variety of activities, including activity label entry, care detail input, sensor data recording, and more. This experiment has 28 action classifications.

In this study, we used several statistical aspects of accelerometer data to identify activities. We've looked at Extremely Randomized Trees as a classification strategy. The first findings are encouraging. However, by shortening the recording time, it is possible to enhance the recognition accuracy. This is a critical problem that we must address in the future. Nursing care records, daily health activity logs, and any work-related tasks are all good candidates for the system's server-side customizability, which makes it relevant to a wide range of industries outside nursing care. This publication presents a dataset that may be used for such studies and analysis.

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