Elderly People Living Alone: Detecting Home Visits with Ambient and Wearable Sensing

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ABSTRACT

Ubiquitous computing techniques are enabling the possibility to provide remote health care services to elderly citizens. In such systems, daily activities are extracted from raw sensor signals, based on which users' health status can be inferred. Due to the ambiguity of raw sensor signals, it is challenging to distinguish the number of people in the ambient, and most such systems assume user live alone. We present an algorithm to automatically detect home visits to elderly people living alone, using an ambient and wearable sensing network. We use visiting reports from caregivers as partially labeled positive data, and conduct statistical analysis to gain insights of visit events in terms of raw sensor data, based on which a set of features are extracted. A one-class support vector machine is trained on a small set of positive data from one user, and tested on five installations. Experimental results show that our algorithm can correctly detect 58%-83% of the labeled visits using only the ambient sensors. The detection rate is improved by incorporating the activity data from Fitbit activity tracker, *i.e.*, with which 75%-87% visiting events are detected. Our system is implemented and tested in the context of a real life health care system.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing theory, concepts and paradigms**; **Ubiquitous computing**;

KEYWORDS

sensor network, visiting detection, Fitbit activity tracker

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1 INTRODUCTION

With the growing population of aging citizens, technology that offers convenient, low cost health services remotely becomes crucial [5]. Due to privacy and cost issues, passive motion sensors are often used in such systems, to capture motion activity. Daily activity and health status information are extracted from raw sensor signals, based on which personalized health care services can be provided.

Visiting is one of the most important activities for elderly people living alone at home, due to the following reasons. First, it promotes social engagement, since loneliness and lack of social interaction is one of the major health issues associated with aging and thus is a serious concern in the health care of elderly patients [10]. Second, knowing if there are visitors at the home of a user also help caregivers plan their regular visits. Third, most of the studies on daily living activities rely on the assumption that the people under study live alone. With the visits correctly detected and excluded from the observations, results of these studies can be improved.

Given the ambiguity of low resolution binary motion sensor signals, it is challenging to detect the number of people at the sensed home, and therefore to detect visits. In [1], multiple motion sensors were installed in a single room office. Raw binary sensor signals captured at each time stamp by each sensor are used as features. Naive Bayes classifier and hidden Markov models are then applied to detect visits. Compared to this installation, ours is a much more sparse setting, i.e. typically only one sensor is installed in each room. In most cases, only one motion sensor is fired at one time stamp, even during a visiting event. Therefore, it is challenging to apply such method to distinguish visits. Room transition at each time stamp is used to detect visiting events in [2]. Similarly, in [3], the authors proposed an unsupervised method for visiting detection using room transitions. A sensor connection topology was carefully designed based on the installation. These systems were tested on one installation. The work in [9] is the most similar to ours. Various features were extracted from 15-minutes windows. Support Vector Machine (SVM) is then conducted on a carefully annotated dataset of positive and negative visits. The main challenge of our problem compared to this work is that we do not have fully annotated data, as in real-life it is challenging and intrusive to label every visit in the life of elders at their private homes.

On the other hand, activity tracking wearable devices have been used in various health care systems [7]. Integrating ambient and wearable sensors has shown to provide improved accuracy for activity recognition in [6], where ear-worn activity sensor data is fused with low resolution vision based ambient sensor signals using a Gaussian Mixture Model Bayes classifier. Recent study investigated using Fitbit for tracking physical activity of elderly people [8].

Our contributions in this paper include the following.
(1) We present an algorithm to automatically detect home visits of elderly people living alone. Our method utilizes a small set of visiting logs from care givers as partially annotated positive examples to train an one-class SVM.
(2) We explore incorporating data from a Fitbit activity tracker to improve the performance of visiting detection.
(3) We study the possibility to apply the model trained on one installation to multiple different installations.

In the following sections, the data collection framework is first introduced, followed with data processing procedures and our methodology, concluding remarks are drawn in the last section.

2 DATA COLLECTION

The ambient sensor system used in the study includes a base unit and wireless sensors which are installed in strategic locations around the apartments. Two types of sensors are incorporated: passive infrared motion sensors (PIR), capable of detecting movement installed at 6 different locations at each participant's home, i.e. bathroom, bedroom, entrance, kitchen, living room, toilet; and door sensors, capable of detecting door open/close activities, placed on the main entrance to detect potential visiting and outing activities, and on the fridge as an indicator of participant's cooking and eating behavior.

Each participant was also provided a Fitbit ChargeHR to capture their daily activity, heart rate, and sleep patterns. Note that Fitbit data is not collected continuously, due to the need to recharge.

Caregivers intervention logs, including the time, duration, type and context of visits are collected on a regular basis. These data are used as partially labeled positive visiting events to train and test our algorithm. Other visiting events are not recorded.

The data used in this study was collected as part of a Swiss-Korean project on healthcare monitoring of elder people in home settings. Selected participants are 70 plus years old living home alone with no pets, who do not need intensive medical attention, and receive at least one home care visit a week. At the time of writing this paper, the project is still on going. We have recruited 20 participants in total. However, we only focus on 5 of them, who have more than one months of data. All data are anonymized and private information is removed prior to any analysis works.

3 PRE-PROCESSING

We collect data from five users since February 2017, with various starting times (second column of Table 1).

3.1 Ambient sensor network

Different rooms at home serve different functionalities in daily life. It is crucial to identify participants' location from the raw sensor data, in order to study their daily activities. We use the location inference algorithm proposed in our previous work [4]. Once a sensor fires, the location of the participant is registered as the sensor's current location. We assume that a participant stays at

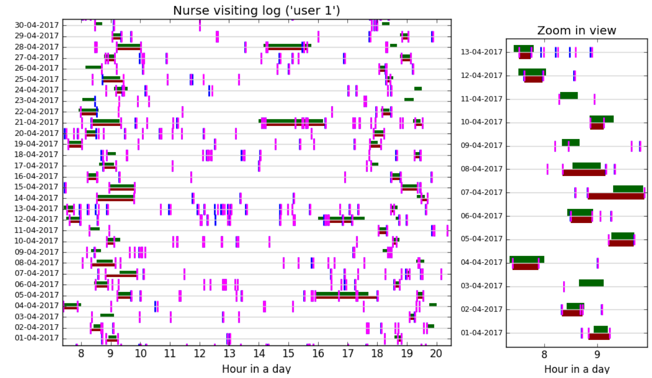

Figure 1: Nurse visiting logs (green horizontal bars), and corrected visiting logs (red horizontal bars). Blue and purple vertical bars indicate door open and close detected at the home entrance.

the current location until sensor installed in another location is activated.

3.2 Nurse visiting logs

We make the assumption that visiting events always happen between two door open/close events at the entrance. No other main entrance into the home is identified. We consider time segments between any two adjacent door events as candidate segments for visiting detection. The vertical blue and purple bars in Fig. 1 show the door open and close events detected in the first installation during the month of April 2017. Note, that a door close event usually happens soon after a door open event, therefore the blue bars are often overlapped with the purple bars. The third column in Table 1 shows the number of door events detected during the data collection period. We disregard any time segment lasts less than 1 minute. The number of resulted effective segments are listed in the forth column of Table 1.

The green horizontal bars in Fig. 1 show the visit logs manually entered by nurses in April 2017. It is inevitable that some errors could be introduced. In order to compensate such errors, we consider the time segments that overlap at least 50% with a nurse visiting log as an effective visit, and correct the starting and ending time of the visiting event with the corresponding door events. The red horizontal bars in Fig. 1 show the corrected visiting logs, which are used as true visits in the following experiments. The fifth and seventh columns in Table 1 illustrate the number of manually recorded visiting logs and the number of effective visits after correction. Note that one reported visiting activity could be splitted into multiple visits due to door events detected during the visit. The sixth and the eighth columns in Table 1 show the accumulated total visiting duration according to the manually recorded visiting logs and the corrected effective visits.

3.3 Fitbit data

The accuracy of using Fitbit to detect physical activity of the elderly has been investigated in [8]. We explore incorporating the active steps with the ambient sensor data for visiting detection. Last

Table 1: Data statistics

UserId	Start time (till: Jun. 06)	# Door open/close	# Effective segments	# Reported visits	Total reported visit length	# Effective visits	Total effective visit length
user 1	Feb. 13	2612	1455	255	110h:01m	283	82h:12m
user 2	Apr. 07	1304	311	55	25h:59m	48	16h:53m
user 3	Apr. 05	636	312	32	13h:00m	17	07h:55m
user 4	Apr. 05	814	496	12	05h:59m	16	06h:06m
user 5	May 02	806	203	75	09h:40m	19	05h:41m

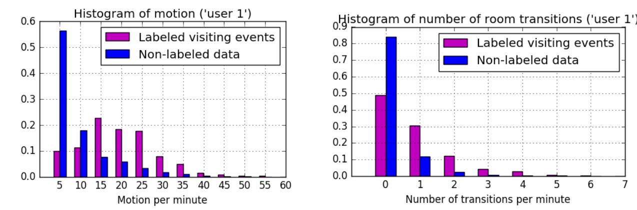

Figure 2: (left) Histogram of average motion detected per minute, in labeled visits and unlabeled data. (right) Histogram of the average number of room transitions per minute, in labeled visits and unlabeled data.

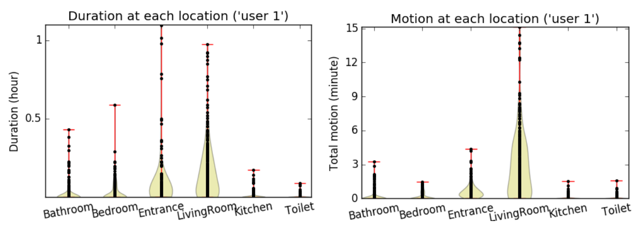

Figure 3: Violin plots showing the distribution of duration (left) and motion (right) at each location of the labeled visits.

column of Table 1 show the total effective time, Fitbit data were collected for each user differently.

Fitbit record the number of steps detected within each minute. In order to synchronize with the motion sensor data, which were collected every second, we compute the average steps per second.

4 DETECTION OF VISITS

4.1 Data analysis

Given the time segments of positive visit events, and unlabeled data for each user, we pose the following questions and conduct statistical analysis to gain insights of the data. First, whether more motion activities could be detected during a visiting event, compared to when the participant is alone. Second, whether there are in general more transitions between rooms with visitors, than when the user is alone. Third, whether the duration of visits is typically bounded in a time range. Fourth, whether visits are more likely to happen during certain periods of time in a day. Last, whether users are more likely to be active at certain locations during visiting events, in comparison to being home alone.

Through the analysis we found different patterns between the labeled visiting events and the unlabeled data. Taking the data corresponding to 'user 1' as an example, we observed the following. First, most visiting events last less than an hour, while the duration of unlabeled segments could last much longer. This is not surprising as nurses who visit elders typically have a tight visiting schedule. Second, visiting events typically happen between 7am to 8pm. Third, there are more than 15 seconds of motion sensor firing per minute for around 80% of the visiting events , while more than half of the unlabeled time segments have less than 5 seconds of motion sensor firing per minute (Fig. 2 (left)). Fourth, on average more than 50% visiting events have on average at least 1 location transition in a minute, while around 80% unlabeled segments have less than 1 transition in a minute (Fig. 2 (right)). Fifth, the entrance and living room have higher usage ratio during visits, in terms of accumulated duration (Fig. 3 (left)) and motion (Fig. 3 (right)), while in the unlabeled data, bedroom, and kitchen usage are also significant.

4.2 One-class classification

Based on the previous analysis, we extract features from each time segment to detect home visits. Specifically, our feature vector is composed of the following components:

- a six dimensional vector encoding the total duration being at each of the 6 rooms during this time segment;
- a six dimensional vector indicating the total number of motion firing at each room individually;
- the number of room transitions; the starting time of the segment; the total length of the segment; and the total number of seconds that motion sensors fired,
- additionally, the total number of steps detected by Fitbit within that time segment.

The nurse visiting logs are used as positive visiting data. However, the unlabeled data may also contain other visiting events, such as social visits by friends and family, house management and food delivery services. Additionally, we do not have definite negative examples. Therefore, in this paper, we consider using the one class SVM algorithm [11] with Gaussian kernel to build model of positive data, and detect visits. It has been successfully used for sensor based anomaly activity detection [12]. The algorithm maps the labeled data into a higher dimensional feature space, and learn a boundary so that most training data lies within the class boundary with an expected error rate.

We use the labeled visiting events of 'user 1' from Feb. 13th till April 30th (206 examples) as training data. Our objective is to learn model parameters so that as much labeled visiting events (training data) are mapped within the class boundary. In practice, on the training set, we achieved detection rate of 90.8% when only the ambient sensor data is used, and 93.7% when the Fitbit data is incorporated.

We first test the trained model on data collected from May 1st till June 6th of the same user. Then, we test whether the trained model can be used in other installations. Transferring the trained model from one user to another is a challenging problem, given the different floor plans, sensor installations, and the difference of participants' daily behaviors. However, it is crucial for new installations when we do not have enough labeled data to train a user specific model. Additionally, it can be time consuming to train user specific model when large number of installations are available.

4.3 Experimental results

Table 2: Detection results

UserId	Labeled visiting		Unlabeled data	
	Ambient	Ambient + Fitbit	Ambient	Ambient + Fitbit
user 1	83.1%	87.0%	44.8%	49.0%
user 2	83.3%	87.5%	28.4%	26.8%
user 3	58.8%	76.5%	15.0%	6.1%
user 4	75.0%	75.0%	22.5%	32.5%
user 5	73.7%	84.2%	15.3%	16.4%

Table 2 shows the percentage of the number of labeled positive visits that are correctly detected and the percentage of segments from the unlabeled data that are detected as visiting events, when only the ambient sensor data is applied, as well as when Fitbit data is incorporated. From the results we can see that, when only ambient sensor data are used, our algorithm is able to detect more than 70% of the labeled visiting events for four out of five installation. The results are improved by incorporating Fitbit data. The different percentage of unlabeled data that are detected as visits indicate the different number of other visits (social, house management, etc.).

From the results of 'user 1' (same user as the training model) we can see that with a small training set, our algorithm is able to detect 87% of the labeled visiting events, at the same time 49% from the unlabeled data are also detected as visiting events. Interestingly, we detected a rather regular pattern of visiting events around middays, which were not reported in the nurse visiting reports. The participant has kindly informed us that indeed she was often visited by her neighbor during midday. This observation has further proofed the value of our system.

By applying the trained model to other different users (last four rows of Table 2), our model was able to detect more than 75% of the labeled visiting events for all installations, and less than 33% from the unlabeled data. When more data becomes available, we are interested in investigating the reasons why it works better for some users than for others. Whether the similarity of floor plans and sensor configuration can be used as an indicator to select the right model for a new installation.

5 CONCLUSION AND FUTURE WORK

This paper proposed a system to detect home visits of elderly people living alone using ambient sensor network and wearable devices. Our algorithm is built and tested on a real life health care system.

We use nurse visiting logs as partially labeled positive data to train an one-class SVM. From the result we can see that our method can detect 87% of labeled visits from newly collected data of the same user. By applying the trained model to other different users, we achieved above 75% detection rate.

As future work, we are interested in investigating the effect of different floor plans, installations to the model selection. And whether it is possible to build a generic model which applies well on most installations.

Our on-going work includes analyzing the automatically extracted daily activity with user's medical record, and personal health assessment (collected via questionnaires), to monitor users' health status and predict any potential health threats, in order to provide efficient personalized health care.

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