Monitoring Elder's Living Activity Using Ambient and Body Sensor Network in Smart Home

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***Abstract*— The high development of medicine causes the world's population aging quickly. To resolve the problem with limited medical resources, constant monitoring of elders' activity of daily living is important. We propose an activity recognition system for smart home, so elders can live alone and their children can monitor their parents' living activity to achieve the concept of "Aging in Place". The living activity monitoring model is powerful to recognize meaningful activities by using both ambient and wearable sensors. It's feasible to deploy in the real living environment because it's a non-parametric learning model. Elders need less effort to label activity in training part, and the model may have chance to find some special activities that the elders did not consider in the past. We demonstrate the living activity monitoring model is feasible to be deployed in a living home with high accuracy performance of the activity recognition result.**

Activity Recognition; Non-parametric Learning Model; Ambient Intelligent; Wearable Computing; Activity of Daily Living; Internet of Things; Ubiquitous Computing; Aging in Place; Tele-healthcare

I. INTRODUCTION

According to the high development of medicine and the success of reducing mortality, the world's population has aged quickly. The elderly people suffer from high risk due to poor health conditions, so the needs for monitoring human's physiological state in non-clinical setting is critically importance [1, 2]. Currently, a large portion of elders live independently. About 72% of elders who are 85 years old or above live by themselves or with spouse in their own houses in United States (the 2012 American Community Survey). Although the concept of "Aging in Place" for elders to live in their own houses has been proposed for long time, the risks the elders are facing still exist, *e.g.* fall, loss of autonomy, etc. Activity of daily living (ADL) is an important factor to estimate the independent ability of elders. Barthel index is used to measure performance in activities of daily living and to assess whether the elders have independent ability [3]. Monitoring the ADL of elders to measure their ability can improve the safe living conditions at home.

The Internet of Things (IoT) is a recently popular issue; it includes the ubiquitous computing where computing is made to appear everywhere and anywhere [4], Ambient Intelligence (AmI) where devices can work in concert to support people in carrying out their daily life activities and tasks more easily, and wearable computing where the associated devices can provide specific, limited features like pedometer, and provide advanced smart function [5]; in our work we use wearable computing to monitor users' meaningful actions. Although ubiquitous computing has been proposed for a decade, relatively fewer researches try to combine both AmI and wearable computing. It's hard to analyze AmI and wearable computing in the same methodology with two reasons. The first reason is that the patterns of ambient sensing data and wearable sensing data are significantly different. The ambient data are usually more static than the data extracted from human body with wearable devices. We can snapshot ambient sensors every-minute to consider the environment information, but we can hardly do the same procedure on wearable sensors. The sensing data from wearable sensors usually have the characteristics of rapid change, so that the analysis on wearable computing needs a design of an efficient and statistic model. The second reason is that wearable computing usually uses only one or two sensors to retrieve information from human body, but the sensors in AmI are usually triggered by fixed events, *e.g.* TV on is usually triggered by the event of watching TV.

In our work, we try to build a smart home based on the technique of IoT. A goal of smart home is to build a robust tele-healthcare system that monitors resident's living activity in real-time. The monitoring result is important for elderly residents because ADL is an important factor to estimate their health state. We have designed a hierarchical activity recognition (AR) model with two-layer structure and it has resolved the problem of combining AmI and wearable computing coherently. The first layer of AR model is to monitor residents' actions from their smart wearable devices through some wearable computing technique. Here, we propose a topic model to consider meaningful actions based on an unsupervised clustering method, named, Dirichlet Process Mixture Model (DPMM) [6]. The topic model is used to retrieve meaningful information from a large amount of temporal/sequential raw data. The second layer of the AR model is to determine the residents' living activities using the result from the first layer and ambient sensors data by a non-parametric clustering method, called X-means [7]. The characteristic of X-means is to find centroid location of each cluster, so that each instance belongs to the closest centroid location. The concept is appropriate for living activity recognition with the ambient sensing data and the meaningful actions simply because the feature distances between two different activities should be high.

The hierarchical AR model also has a special characteristic which is that such model does not require a prior specification of the cluster number. It's an important factor for elderly residents to set this system in a real living environment. The non-parametric clustering algorithm means users do not need to set the specific number as the number of activities to be recognized. It is apparently very different from both supervised learning method and parametric clustering; such as k-means algorithm. The non-parametric learning method will find the most appropriate number of clusters based on their training data. It's suitable to model the problem in the realistic world. In our work, we try to monitor elders' living activities, but it's hard to ask them to label their activities for every instances in the training course. Since the proposed AR model can find the significant living activity of each cluster, a direct advantage is that elders only need to specify the resulting clusters in a very straightforward manner. For an elder who lives alone, deploying the hierarchical AR model is apparently easier than the parametric model.

The remainder of the paper is as follows. The materials of our system are described in Section II. The two main methodologies of the hierarchical activity recognition model are described in Section III. And a simple experiment that evaluates the proposed hierarchical AR model is shown in Section IV. The result of the AR model not only finds all significant activities without labels and parameters, but also obtains a promising accuracy rate performance of the recognition. In Section V, we make a brief summary of the proposed hierarchical AR model and discuss the future work.

II. Materials

This section will describe the material sensors used in our activity recognition methodology. We have established a smart home environment to collect the ambient data and let the user to wear a smart watch with accelerator inside to real-time collect his/her vital sign information.

A. *Ambient Sensor Network*

As mentioned, we have established a smart simulation home in our laboratory, whose layout is as shown in Figure 1. That environment specifically consists of 4 rooms, namely, living room, studying room, kitchen and bedroom. In the previous work, we designed a simple smart meter on the embedded device "Taroko" that is used to monitor the on/off status of each electric appliance. Moreover, each room has been equipped with temperature, lumen and humidity sensors. The entrance door has also been mounted a switch sensor used to monitor the activities of "go out" and "come home". Those sensors in the previous research work are developed to research on how to save energy, unlike this work where we try to use them to monitor elders' living activity.

The ambient sensors in our work have been divided into two different categories, of which one is mainly to monitor the living environment, *e.g*. lumen sensors used to monitor light level for each room and switch sensors equipped on the entrance door used to determine whether the resident goes out, comes home, or else, and the other is mainly to monitor the active state of electric appliances so that the residents' activities will be revealed when the associated electric appliances are being used. An example of the latter is that the AR system recognizes that the resident is watching TV partly because it finds the state of TV is "on".

B. *Body Sensor Network*

In order to realize specific physical activity of an elder, using the wearable sensors to collect their vital sign is necessary. Note

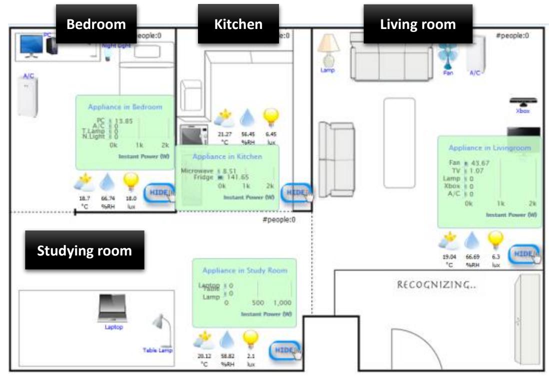

Figure 1. The 2D ichnography of our smart simulation home

that ambient sensors themselves are usually embedded into environment, whereas wearable sensors are directly attached to the human body, which typically can run continuously and can be operated hands-free [8]. While those embedded devices and wearable devices communicate and cooperate with each other, the original monitoring system is now enhanced to serve as a seamless monitoring system.

In this study, the wearable sensor we adopted is a smart watch made by "Golden Smart Home Technology Corp.". It is equipped with a tri-axial accelerometer and low energy Bluetooth with 30 Hz sampling rate. We have preprocessed those acceleration data of each axis to obtain mean and variance every 0.5 second. Each pattern extracted from the accelerometer inside the wrist watch indicates a waving motion of arm, and the numbers of consecutive waving motions can be associated with a specific activity. A clustering method called Dirichlet Process Mixture Model (DPMM) is used to categorize the waving motions, and the results will serve as new features for activity recognition. The detailed processing procedure will be described in section 3.A.

III. Methods

In this section, we describe the methodologies of activity recognition model. First, we will describe the Dirichlet process mixture model to categorize the waving motions of arm. Because the number of consecutive waving motions can be associated with one specific activity, the DPMM has been designed as a hierarchical architecture to determine the activity without ambient sensors. The second part will describe a clustering learning model, called X-means, to recognize more specific activities with integrated ambient and wearable data.

A. *Dirichlet Process Mixture Model*

The topic model can be used to automatically extract activity pattern from the sensor data and then to recognize those daily routines [9, 10]. We take the tri-axial acceleration data collected every second as "word" in the topic model, and three words mapped to 3-axis as a vocabulary. Each topic must include several identical types of vocabularies, *i.e*., one topic can be seen as one activity, such as walking, sitting, standing and eating meal, etc. We propose a topic model to recognize meaningful action from acceleration data. The topic model is constructed by two layers Dirichlet process mixture model (DPMM), called 2LDPMM. In the first layer of 2LDPMM, it can extract categories features from raw data. For example, people have different kinds of hand's waving motion, such as drooping hands, horizontally waving hands, vertically waving hands or show of hands. It's hard to define the specific number of kinds of hand's waving motions. 1st-Layer DPMM is used to learn hand's waving motions because DPMM is a non-parametric unsupervised clustering model. It can find different kinds of hand's waving motion from raw data without given a specific number of motion types. The continuous and temporal data is hardly extracting to useful information in traditional unsupervised clustering methods. The second layer of 2LDPMM is going to reduce this drawback. The training feature of 2nd-layer DPMM are grouped by 60 continuous output from 1st-layer 2LDPMM. We calculate the occurrence time of each waving motion from 1 minute result of first layer, and construct the statistic result as the feature of 2nd-layer 2LDPMM. The statistic of waving motion can be seen as a meaningful action of user's body behavior; says, people usually have changeless waving motions to do a specific action, *e.g.* while sitting, hands usually place on thigh fixedly; while sweeping, hands whip regularly; while having meal, hands put on table sometimes and take the bowl sometimes. Figure 2 shows the histograms of waving motions of three meaningful actions. The daily activities of reading and watching TV have similar histograms because their body behavior are similar and called sitting.

We use 2LDPMM to recognize body behavior with two reasons; first, Dirichlet process mixture model can find meaningful cluster without given the number of cluster; second, it's a powerful clustering method to retrieve latent information from raw data. Before describing DPMM, we will introduce the Dirichlet distribution and Dirichlet process. A Dirichlet distribution Dir(α) is a distribution over multinomial, and it can be seen as the multivariate generalization of the beta distribution. It's a family of continuous multivariate probability distributions parameterized by a vector α of positive reals. This means when the parameter of a data point is distributed as Dirichlet, the posterior distribution of the parameter will be a Dirichlet. Its probability density function returns the probabilities of K rival events are π_i given that each event has been observed $\alpha_i - 1$ times. Dirichlet distribution is the conjugate prior distribution of multinomial distribution.

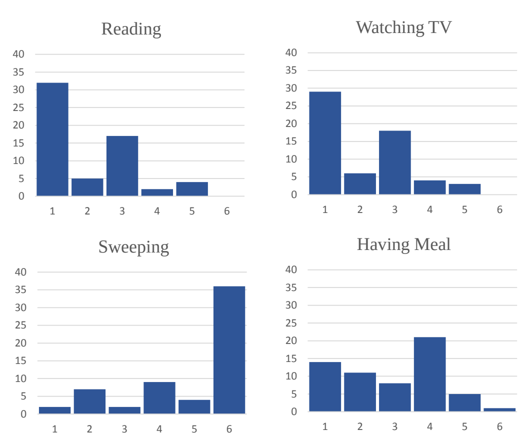

Figure 2. Four types of activities' histograms: aggregated 1st-layer 2LDPMM results as new feature for 2nd-layer 2LDPMM; the horizontal number means the waving motions found in 1st-layer 2LDPMM; the vertical number means the occurrence time of each waving motion.

There are existing the number of successes in a certain number of N trails. That N is the number of a sequence of independent data and each data with probabilities $p_1, \ldots, p_k$; Multinomial models the distribution of the histogram vector which indicates how many time each outcome was observed over N trials of experiments.

$$P(x_1,...,x_k|n, p_1,...,p_k) = \frac{N!}{\Pi_{i=1}^{k} x_i!} {p_i}^{x_i} \text{ and } \sum_{i=1}^{k} x_i = N \quad (1)$$

Dirichlet distribution is parameterized by a vector of $A = \{\alpha_1,\ldots,\alpha_k\}$, where $\alpha_i \geq 0$ and $K \geq 2$. Define a random vector $\Pi = \{\pi_1,\ldots,\pi_K\}$, where $\sum_{i=1}^{K} \pi_i = 1$, $\pi_i > 0$ and $\pi_i \in [0,1]$. The Dirichlet distribution with vector A has a probability density function $P(A)$ shown as follows:

$$P(\alpha_1,...,\alpha_K) = \frac{\Gamma(\sum_i^K \alpha_i)}{\Pi_i^K(\Gamma(\alpha_i))} \sum_{i=1}^{K} {\pi_i}^{(\alpha_i - 1)} \quad (2)$$

So π is mapping to the probabilities p of multinomial. We say that Dirichlet is the conjugate prior of multinomial. And the support of K dimensional Dirichlet distribution is the K-1 dimensional probability simplex. Let $\Pi=(\pi_1,\ldots,\pi_K) \sim \mathrm{Dir}(\alpha)$, meaning that the first K-1 components have the above density and the weight of π_K should be defined as follows:

$$\pi_K = 1 - \sum_{i=1}^{K-1} \pi_i \quad (3)$$

The Dirichlet process is an infinite-dimensional generalization of the Dirichlet distribution and it is denoted as DP(α,H), where α is a positive real number called the concentration parameter and H is a base distribution. The base distribution is the expected value of the process, *i.e.*, the Dirichlet process tries to draw distributions around the base distribution. And, the concentration parameter used to specify the strong level of the discretization, such as in the limit of $\alpha \to 0$ means the realizations are all concentrated on a single value. On the contrary, in the case where limit of $\alpha \to \infty$ means the realizations become continuous.

The Dirichlet process mixture model generalizes a mixture model with infinite mixture components. A mixture model is a hierarchical model, and it's a probabilistic model for representing the presence of subpopulations within an overall population [11]. Mixture models are used to make statistical inference about the properties of the subpopulations given only observations on the pooled population, without subpopulation identity information. And, it consists of the following components:

K = number of mixture components
N = number of observations
θ_i = parameter of distribution of observation associated with component i, for $i = 1,\ldots,K$.
ϕ_i = mixture weight
Φ = K-dimensional vector composed of all the individual $\phi_{1\ldots K}$
z_i = component of observation i
x_i =observation i
$f(x|\theta)$ = probability distribution of an observation
$z_i \sim \mathrm{Categorical}(\phi)$
$x_i \sim f(\theta_{z_i})$

A data point x_i is drawn from the distribution $P(x)$.

$$P(x) = \sum_{k=1}^{K} \phi_k f(x|\theta_k) \tag{4}$$

When the mixture weight $\Phi = \phi_1, \ldots, \phi_k$ is multinomial distribution, we can use the Dirichlet distribution as its prior. In DPMM, the number of mixture components is infinite, so the original mixture model needs to be modified as follows:

$$\begin{gathered}\theta_{z_i} \sim \mathrm{H} \text{ for } z_i=\{1,\ldots,\mathrm{K}\}, \\ \phi_1,\ldots,\phi_K \sim \mathrm{Dir}(\alpha/K,\ldots,\alpha/K), \\ z_i \sim \mathrm{Multinomial}(\phi_1,\ldots,\phi_K), \\ x_i \sim f(x|\theta_{z_i})\end{gathered} \tag{5}$$

In the limiting case, $k \to \infty$, the finite number of K becomes infinite. The Dirichlet process as shown in the following steps:

$$\begin{gathered}G \sim \mathrm{Dir}(\alpha,H), \\ \theta_i \sim G, \\ x_i \sim f(x|\theta_i)\end{gathered} \tag{6}$$

The prior distribution function G is drawn from a Dirichlet process and, α is the concentration parameter, and H is the base prior. Given G, x_i belongs to θ_i, and we sample θ_i to the components. Then, given θ_i, we generate each data point x_i from acceleration features. For implementation of DPMM, we use an open API called Dataumbox to train our arms' waving motions. Its DPMM uses Gibbs sampling algorithm and we build the Dirichlet process by Chinese restaurant process [12].

Using DPMM twice is seen as one topic model called 2LDPMM. The first layer of 2LDPMM is used to extract pattern from raw data; before processing the second layer of 2LDPMM, we aggregate those patterns from the first layer into a time-windows. The aggregated data represent the pattern distribution over every time-window and consider as new feature for the second layer DPMM. The result of each cluster means a meaningful topic. In our work, it means the meaningful actions, *e.g.* sitting and sweeping.

B. *X-means*

The X-means is an extended K-means that without assigning the number of clusters. K-means is a famous method of vector quantization used for unsupervised clustering learning [13]. It aims to partition totally n observations into k clusters. Each cluster will get a mean value, so that each observation will be assigned to the cluster whose mean is the nearest and serves as a prototype of that cluster. However, the drawback of this powerful clustering method is that we need to assign the number of clusters K. In the realistic world, it's hard to estimate the number of the clusters, or the number of interested activities in this research. X-means has resolved the problem which efficiently searches the space for the cluster locations and the number of clusters to optimize the Bayesian Information Criterion (BIC) measure [14]. In fact, X-means produces better result both in synthetic occasion and real-life than traditional K-means.

The naive K-means algorithm initializes the random values to the centroids in the first iteration. All data-points will find the closest centroids for every-iteration, and then the data points are associating to the closest centroids, respectively. Next, we re-estimate each centroid location by evaluating the center of mass of points associated with it. Keep track of the centroids of the

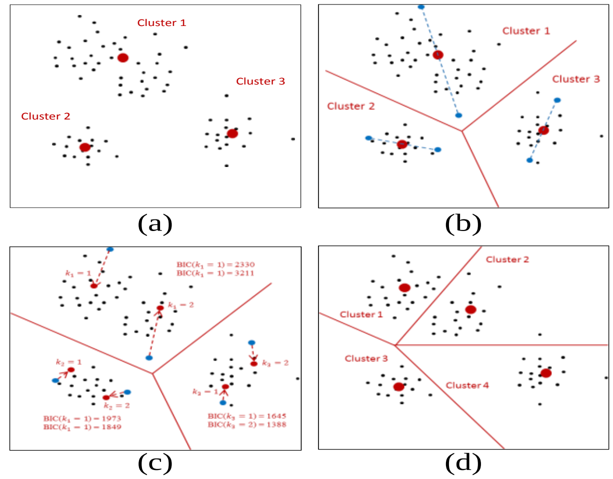

Figure 3. A sample of split procedure when X=3, (a) Existing 3 clusters; (b) split each centroid and blue nodes as children centroids; (c) red nodes are the new centroids using 2-means algorithm and calculate their BIC value; (d) split result and the cluster 1 had been split into 2 new centroids

subsets, and continue the iterations. The algorithm terminates when the centroid locations stay fixed for a number of iterations.

For X-means algorithm, we need to give a lower bound and an upper bound as the number of clusters a priori. In the process, it stars with the lower bound number, which can be deemed as the number K of K-means algorithm, and continues to add centroids where they are needed until it reaches the upper bound number. Moreover, the best score of the centroid set has recorded, and it becomes the final output. In this research, we add two new operations to X-means algorithm, namely, Improve-Params and Improve-Structure, of which the former is to run the conventional K-means algorithm till it converges, whereas the latter is used to find a new centroid should appear. In particular, the latter operation picks some set of centroids and splits each into two sub-centroids. When it chooses every centroid and split it into two centroids, the algorithm separates every cluster in an individual space and proceeds with a K-means (K=2) to find new centroids for each space. Then, one uses a measurement score BIC to determine whether the new centroids can survive or not. After the process of Improve-Structure, if the number of clusters x is higher than the upper bound number, the algorithm terminates and outputs the best-scoring model during the search. Else, it starts a new iteration that calls for Improve-Params and Improve-Structure again.

The decision criteria of splitting a centroid into two new centroids is according to some heuristic rule. We use Bayesian Information Criterion (BIC) to measure the scores for each split, and if the resulting model scores better than the original, then we accept the split. The BIC value is used to find each cluster similarity. Figure 3 is a simple example of the splitting procedure and X = 3.

C. *The Hierarchical Activity Recognition Model with Dirichlet Process Mixture Model and X-means algorithm*

We have described two unsupervised learning models, Dirichlet Process Mixture Model (DPMM) and X-means algorithm. Both of them are quite plausible in realistic world because they do not need prior assignment of the specific number of clusters. In the real world, it's hard to determine the number of kinds that

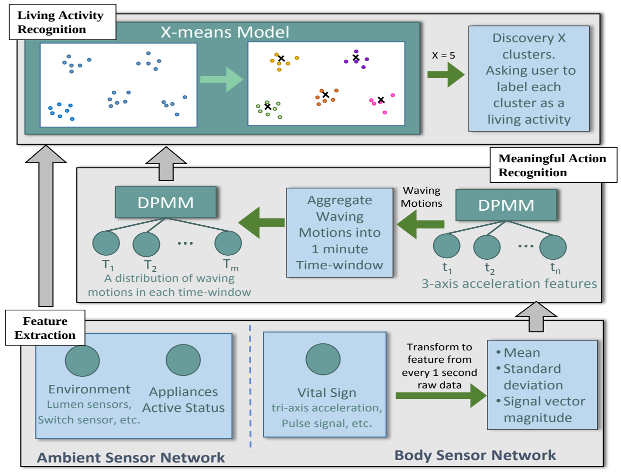

Figure 4. The Flow Path of the Hierarchical AR Model

we want to observe. For example, the sensing data collected from wearable and ambient sensors can represent different activities. For implementation, one normally input a number of activities to train the learning model. However, some activities may occur only for one or few times in the real living home, and the training model would not determine them correctly. For example, an elderly lady sometimes sweep and turn on TV in the living room, but we will not define this kind of aggregate activity in the training part. Thus, the traditional activity recognition model will not be able to observe this aggregate activity. If a learning model can observe activities without assigning specific number of clusters, it may have chance to find all meaningful activities in the real life. Therefore, we propose a hierarchical activity recognition model using wearable sensors and ambient sensors to monitor elders' living activities in their real life.

The hierarchical activity recognition model is composed by 2LDPMM and X-means, and Figure 4 shows its flow path. The first layer is DPMM structure model is used to cluster the tri-axial acceleration data from the wrist, and the clustered results represent the waving motion of an arm. The features of the first layer model are the average standard deviation of the tri-axial acceleration data during one second as well as the signal vector magnitude [15] that shows the power of motion. After training, we find every second's waving motion of arm. Then we aggregate those clustered results as a distribution during every minute. Using those distributions as a new feature to train the DPMM again, we obtain the result that can represent some meaningful actions, such as sitting, standing or swinging hands.

The second layer model is constructed by X-means algorithm. In this layer, we add ambient sensors data and those meaningful actions extracted from first the layer as features. The environmental changes is generally slower than that of the body movement. We snapshot ambient sensors every one-minute to get the lumen value of every rooms and the activation status of all electric appliances. The sensing lumen value l_r between 0 to 255 in each room, and the active status of the electric appliance ea_n are "off $(ea_n = 0)$", "standby $(ea_n = 1)$" and "on $(ea_n = 2)$". Moreover, the clustered results of the meaningful actions become new features to X-means model. The result of second layer is mapped to one of daily activities and it shall include one meaningful action that represents the body behavior. *e.g.*, in the first layer, it finds 6 clusters and an activity belongs to one cluster, then this activity can be converted to X-means features as $A = \{a_1 = 1, a_2 = 0, a_3 = 0, a_4 = 0, a_5 = 0, a_6 = 0\}$. Different activities have diverse distributions of all features, so we can use X-means to find the centroid's location of each feature. We have compared this unsupervised learning model with the supervised one, and find that the former does not yield to the latter.

IV. EVALUATION

A. Data Collection

In the experiment, we have collected 2 hour data in our smart home with 8 defined activities show in TABLE I. Each instance sustains for one minute. Sweeping take place in two locations, namely, studying room and living room, and the ambient situations of sweep and of watching TV are the same.

B. Result

For the hierarchical activity recognition model, we train the tri-axial acceleration data by first layer model. The result is shown in TABLE II. We could find that these clusters from 1 to 16 some can directly correspond to activities. However, some activities are still hard to distinguish by the information of acceleration. If two activities have same behavior of user's hand, we cannot distinguish them. In the experiment, the activities of

TABLE I. TYPES OF EXPERIMENTAL ACTIVITIES

Location	Activity	Location	Activity
Living Room	Watch TV	Study Room	Read book
	Do exercise		Play pad
	Read newspaper		Sweep
	Meal	Kitchen	Wash dishes
Bedroom	Sleeping	Hallway	Go out

TABLE II. THE CLUSTERING RESULT OF MEANINGFUL ACTION

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Watch TV	0	0	0	7	0	0	0	21	41	0	0	0	0	0	0	0
Read Newspaper	0	2	0	2	0	0	0	0	54	4	0	0	0	0	0	0
Exercise	115	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Meal	0	0	9	76	12	26	101	1	0	0	0	0	0	0	0	0
Play Pad	0	0	0	40	0	0	0	87	4	3	0	0	0	3	0	0
Read Book	0	2	0	9	0	0	0	0	108	3	0	0	0	0	0	0
Sweep	0	0	0	0	0	0	0	0	0	10	56	0	0	0	0	0
Sleep	0	0	0	0	0	0	0	0	0	0	0	13	286	0	0	0
Wash Dishes	0	0	4	0	0	0	0	0	0	0	0	0	0	4	164	0
Go Out	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	56
Other	0	1	2	2	0	0	0	1	0	5	0	3	0	1	0	0

TABLE III. THE CLUSTERING ACCURACY RATE FROM X-MEANS WITHOUT THE FEATURE OF MEANINGFUL ACTION

	C1	C2	C3	C4	C5	C6	C7	C8
Watch TV	69	0	0	0	0	0	0	0
Read Newspaper	0	62	0	0	0	0	0	0
Exercise	0	0	114	0	0	0	5	0
Meal	0	0	220	0	0	0	5	0
Play Pad	0	0	0	133	4	0	0	0
Read Book	0	0	0	0	126	0	0	0
Sweep	2	0	0	0	63	1	0	0
Sleep	0	0	0	0	0	293	0	6
Wash Dishes	6	0	0	0	0	0	166	0
Go Out	0	0	0	0	0	0	0	59
Other	8	0	0	4	0	0	0	3

TABLE IV. THE CLUSTERING ACCURACY RATE OF X-MEANS

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Watch TV	21	42	0	0	0	0	0	0	6	0	0	0	0	0
Read Newspaper	0	0	62	0	0	0	0	0	2	0	0	0	0	0
Exercise	0	0	0	119	0	0	0	0	0	0	0	0	0	0
Meal	0	0	0	0	26	107	90	0	0	0	0	0	2	0
Play Pad	0	0	0	0	0	0	0	89	45	3	0	0	0	0
Read Book	0	0	0	0	0	0	0	0	2	124	0	0	0	0
Sweep	0	0	0	0	0	0	0	0	0	0	64	0	0	2
Sleep	0	0	0	0	0	0	0	0	0	0	0	297	0	2
Wash Dishes	0	0	0	0	0	0	0	0	0	0	0	0	172	0
Go Out	0	0	0	0	0	0	0	0	0	0	0	0	0	59
Other	1	0	0	2	0	0	0	1	3	0	1	1	2	4

"Read newspaper" and "Read Book" are same that both they are reading something in different rooms. And the behaviors between "Watch TV" and "Read" are similar, so the cluster C9 identifies three activities: "Watch TV" "Read newspaper" and "Read Book". And "Watch TV" sometimes is similar to "Play pad", so the cluster C8 identifies "Play pad" and "Watch TV". Even though the vital sign part AR model can almost recognize both Posture and Motion activities, some activities are still hard to be correctly recognized. In contrast, we consider the appliance usage states or light on/off in different rooms, and these features use to train the ambient part AR model. Table III shows the predicted results of ambient part AR model. The ambient part AR model finds 8 clusters, and each cluster represents one to two activities. If two activities use same appliance and stays in same room, they are belonging to same cluster. For example, "Exercise" and "Meal" are both staying in living room and they are not using any electronic appliance, so they are belonging to the cluster "C3". And this is the reason that only using ambient sensor is hard to identify various activities of daily living. Table IV shows the clustering results fusing ambient and vital sign data. It observes 14 clusters, and each cluster represents a categorized training data. Each categorized training data is mapping to one daily living activity. The average accuracy is up to 97.48%. It examines that we can use the categorized clusters for user to label data and also label the mapping service to complete the healthcare system.

V. CONCLUSION

We hereby proposed a model to monitor the activities of daily living for elders in their home environments. The material sensors for the model are roughly divided into two groups: one is used to monitor the environment called ambient sensors, whereas the other is used to monitor the human body called body sensors. The monitoring model has fused these two different types of sensors by using a hierarchical activity recognition model. The first layer of the activity recognition model is built by two layer Dirichlet Process Mixture Model (2LDPMM) and it's used to recognize the human behavioral activities with the tri-axial acceleration data collected from a smart watch. The first layer results represent some meaningful actions, such as sitting, standing or swinging hands. The second layer of the activity recognition model is built by X-means algorithm and it's used to recognize the living activity based on the first layer results and the ambient sensors data, such as meal, reading, sleeping or sweeping. Our activity monitoring model is more appropriate for real living environment because our activity recognition model does not need to specify priory the number of the cluster in order to train the model. The experiment has demonstrated the system's ability to build in real living environment. It can recognize more activities using both ambient and body sensors than using only one type of sensor. Moreover, its accuracy rate is up to 97.48%, which suggests that the proposed hierarchical AR model is feasible to monitor elders' living activity in a smart home environment for the realization of the concept: "Aging in Place".

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