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基於智慧空間之銀髮族日常生活活動觀測照護系統

Activity of Daily Living-aware Elderly Health   
in Pervasive Environment

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1. 中文摘要

由於醫療進步與致死率降低，人口老化現象逐步加劇，且隨著許多國家伴隨著少子化現象，導致年輕族群將面臨撫養多位長者巨大的壓力。且老年族群若伴隨著不良的生活型態將有較高的致死率，故在非臨床環境下能隨時隨地監測年長的的生理狀態將帶給家屬與醫護人員許多的幫助。故本研究將致力於開發一套具有自動監測環境中長者日常生活活動的智慧環境照護系統，提出一整套創新的非監督式學習活動辨識多階層模型，用以解決以往活動辨識標記活動之困難與適應性功能，能夠隨著長者生活型態改變重建學習模型。也本研究將整合穿戴式感測器與Ambient感測器兩類型異質感測器整合分析方法，改良以往單種感測器之活動辨識方法，並與物聯網(Internet of Things)理念整合，在未來世代將可更全面建置智慧環境，本系統將可輔佐瞭解居住者的生活型態，並可在未來發展用以監測異常狀態或異常生活型態，逐步提升居住者的健康狀態。

**關鍵字**:在地老化、活動辨識、適應性學習模型、智慧照護系統、物聯網

1. ABSTRACT

**Keyword:** Smart Grid, Demand Side Management, Renewable Energy, Peak-to-Average Ratio

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# Introduction

## Motivation

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](#_ENREF_1), [2](#_ENREF_2)]. With the declining birthrate phenomenon, taking care of elder family will gradually bring burden and pressure for their children. Currently, a large portion of elders live independently. That is the reason of most adults and elders would prefer to age in place which means remain in their home of choice as long as possible. 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). The institution “Centers for Disease Control and Prevention (CDC)” defines aging in place as “the ability to live in one’s own home and community safely, independently, and comfortably, regardless of age, income, or ability level.” 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. Technology can be an important role for aging in place to assist elders in their own home. There are four categories of technology for aging in place—Communication and Engagement, Health and Wellness, Learning and Contribution, and Safety and Security. The high development of activity recognition technology is able to build a daily activity monitoring system in home environment. 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](#_ENREF_3)]. Monitoring the ADL of elders to measure their ability can improve the safe living conditions at home.

Wireless sensor network (WSN) is a well-developed technology in recent years and a lot of interesting products has been proposed, *e.g.* mobile pad, smart watch or raspberry Pi with ambient sensors. With the technological development of WSN, the Internet of Things (IoT) has more space to play well. The Internet of Things includes the ubiquitous computing where computing is made to appear everywhere and anywhere [[4](#_ENREF_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](#_ENREF_5)]. The technology of IoT is an important factor to implement a smart environment to monitor residents’ daily activity.

## Challenges

In order to implement a friendly and automatic daily activity monitoring system in smart environment, three primary challenges have to be addressed. The first challenge is to achieve more activities to recognize with higher resolution of integrating ambient and wearable sensors data. The second challenge is to achieve lower cost on labeling activity when users build activity learning models. The final challenge is to propose an automatic learning framework, i.e. this framework can automatic identification of activity that has not been seen, and add it to the activity recognition model.

### Integrating Ambient Sensor Network and Body Sensor Network

In order to identify more precise activity of user for our system, adopting both ambient sensors and body sensors in same time is necessary. The ambient sensors records environment information as an objective point of view to monitor users daily activity; the body sensors—wearable sensors, pulse sensors, etc. —records vital sign of body and they shows the subjective point of view to monitor users daily activity and health status. The technology of analysis ambient sensors called Ambient Intelligent (AmI); and the technology of analysis body sensors called Wearable Computing. In our work, we use both of two type sensors to monitor users’ daily activity. 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.

### High Cost on Labeling Activity

Supervised model is usually used in the methodologies of activity recognition in smart environment. Supervised learning is a procedure using labeled data to construct a mapping function, which can be used for mapping new instance. Its training data needs to be labeled their ground truth before building the supervised learning model. When the training data is abundant, the inferred results of supervised learning model usually performs well. However, labeling amount of data is a burden task and wrong labeling training data makes a poor classifier. It is also hard to remember daily activities per day in real life. These negative features make the activity recognition in smart environment becoming an experimental application though it is a popular issue for Internet of Things. Some research try to resolve the high cost on labeling data. They adopt unsupervised learning method to build the activity recognition model, *e.g.* k-means algorithm, Gaussian mixture model, etc. Unsupervised learning is used to find hidden structure in unlabeled data. The drawback of unsupervised learning is that it is necessary a specific number of activity to build unsupervised learning model. If given a wrong parameter to build unsupervised learning model, it would become a poor inference model. It is hard to choose a better performance parameter of unsupervised learning in real life.

### Adaptive Learning of Activity Recognition Model

Automatic activity monitoring is the ideal goal for elderly home care. The function of adaptive learning is an important role for automatic activity monitoring system. With aging, elderly people may have new lifestyles. For built activity monitoring system, those new activities are unseen activities. If the system without adaptive function, it is not suitable for elderly people to use. Adaptive learning is an educational method which uses computers as interactive teaching devices, and to orchestrate the allocation of human and mediated resources according to the unique needs of each learner. In smart environment case, the adaptive learning algorithm of activity recognition model can identify unseen data and consider it as a new type of activities. The adaptive learning model includes two principle functions: discovering new activities and adding data of new activities into training data set to rebuild the learning model. These two functions are both important for elderly home care. If elderly people occur an anomaly behavior, the function of discovery can help his/her offspring get the emergency alert from the monitoring system. The second function can record new activity as seen activity, so the monitoring system will not ask user to identify this activity again. If this activity occurs in the future, the monitoring system can recognize this activity automatically. However, the application of elderly home care system activity

## Related Work

## Objective

In this thesis, we try to build a smart home environment based on the technique of IoT. The goal of smart home is to build a robust tele-healthcare system that monitors resident’s living activity in real-time. For the purpose of addressing the aforementioned challenges, the objective of this thesis is to develop an Activity of Daily Living-aware Elderly Care Home System as a powerful smart environment application. The system aims to monitor residents’ daily activities anytime in their house; the system aims to observe the lifestyle of residents and report their anomaly behaviors. The contributions of this thesis are listed as follow:

### Better Recognized Performance by Sensors Fusion

The activity monitoring result is important for elderly residents because ADL is an important factor to estimate their health state. To analyze activity of daily living (ADL) of elderly peoples can help caregivers estimate their health conditions. Different sensors can observe different points of view on residents in home environment. In other words, it is necessary to fuse heterogeneous sensors to observe more precise activities. For ambient sensors, they usually observe objective point of view that means they monitor residents’ activity in their home in indirect way. The observations from ambient sensors are usually triggered by specific activity, so the ambient data analysis belongs to event trigger orientation. For wearable sensors or other vital sign monitoring sensors, they usually observe subjective point of view that means they monitor residents’ activity in direct way. The observations from wearable sensors are unlike to ambient sensors. To observer an activity needs a set of continuous wearable sensor data. A few sensors can be built on wearable devices, and each sensor data have high degree of correlation. This characteristic makes wearable data analysis hardly using same methodology of ambient data analysis. Both ambient intelligent (AmI) and mobile computing are highly developing independently, but they are rare to fuse together with their totally different characteristics. We have designed a hierarchical activity recognition (AR) model with two-layer structure and it has resolved the problem of combining AmI and mobile computing coherently. The first layer of AR model is to identify residents’ behaviors from two activity recognition models: environment-based AR model and body-based AR model. The environment-based AR model determines the residents’ living activities from ambient sensors data through an unsupervised learning algorithm with fuzzy learning. The body-based AR model collects wearable sensor data from residents’ smart wearable devices through some wearable computing technique. Here, I propose a topic model to consider meaningful actions based on an unsupervised clustering method, named, Dirichlet Process Mixture Model (DPMM) [[6](#_ENREF_6)]. The topic model is used to retrieve meaningful information from a large amount of temporal/sequential raw data. 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. Before building the second layer of the hierarchical AR model, the system will fuse results of environment-based and body-based models as new format of training features. The second layer AR model is used to determine residents’ living activity in an overall view. These two-layer AR model can determine precisely activity for residents, *e.g.* If one is watching TV and sweeping at same time, then analysis of ambient data can only determine the active status of TV and analysis of wearable sensors can only determine the resident is doing the activity of sweeping. Fusion ambient and wearable data analyses can determine both two activities.

### Facilitated Activity-aware System for Elderly Healthcare

For elder people, learning to use technology products is greater obstacles than younger people. Simple and automated system for elderly people is a more approachable. In order to reduce the burden on elderly people learning to use the activity-aware healthcare system, the system has easily labeling function and discovery new lifestyle function. These two novel functions make elderly people independently use healthcare system by themselves.

To achieve friendly labeling function, the system avoids complex and time consuming procedure on labeling all training. In training mode, the AR model learns activities by data-driven without labeling training data. Data driven means that progress in an activity is compelled by data, rather than by intuition or personal experience. This is the main reason that the hierarchical AR model adopts unsupervised learning methodology. And it also has a special characteristic which is that such model does not require a prior specification of the cluster number. 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 an important factor for elderly residents to set this system in a real living environment. 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. The system 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.

To achieve discovery new lifestyle of residents, the system adopts adaptive learning to discover activity which is out of training data and rebuild the activity recognition model. In online mode, the activity-aware system has a mechanism called case-based reasoning (CBR). Case-based reasoning is an artificial intelligent technology, it is the process of solving new problems based on the solutions of similar past problems. CBR of the activity-aware system is used to discovery unknown cases and immediately provide service based on the most similar case. After the system provides service, it will ask resident what meaning of activity is. When this activity has been labeled, the AR model is going to be rebuilt. The activity-aware system can identify this activity from the re-new AR model. The automatically discovering mechanism is suitable for elderly residents because their aged process usually accompany with new habits and behaviors.

## System Overview

In order to address the activity-aware healthcare system, I proposed two modes of the system: training mode and online mode. The training mode is used to identify activities from data automatically as a number of clusters. Each cluster presents a meaningful activity. Residents need to apply training mode before the system monitors their daily activity. Training mode model will provide an interface to label each cluster’s mapping activity. After residents label all clusters, the online model will be generated by those labeled data.

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|  |
| Fig. ‑ System Overview of Training Mode |

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| Fig. ‑ System Overview of Online Mode |

The online mode is used to real-time determine activity of elderly residents and monitor anomaly activity. If an unknown activity has been observed, the system will determine whether it is an anomaly activity or not. If the unknown is similar to those anomaly activity, the system will send an alert message to the elderly resident’s caregiver. And the system will require resident to label this activity and retrain the AR model. The following Fig. 1‑1 and Fig. 1‑2 show the system overview of training mode and online mode.

Before building the hierarchical AR model, extracting feature is an important part. In machine learning, feature extraction starts from an initial set of measured data and builds derived values intended to be informative, facilitating the subsequent learning. The ambient sensor data is extract as Boolean variable: on and off, because they are triggered by human activity, *e.g.* current sensor on Television measures low power when Television is close; but measuring high power when Television is open. A simple classifier is proposed to determine the state of Television by its current sensor data. The wearable sensor data is extract as some statistic variable or physical feature, such as a second mean and variance data.

## Thesis Organization

This thesis consists of five chapters, and they are organized as follows.

**In chapter2**, we introduce some preliminary knowledge of the thesis, includes pervasive environment, non-parametric statistic distribution: Dirichlet distribution, unsupervised learning methodologies: Mixture Model, K-nearest neighborhood and supervised learning methodology: Conditional Random Fields.

**In chapter3**, we describe the detail of our hierarchical activity recognition model. The feature selection of recognition model is described in this chapter. The feature of ambient activity recognition needs to be transformed to Boolean variable, i.e. the current sensor of Television usually detects value lower than 10 Watts that respects TV is close. When TV is open, the current sensor detects value higher than 40 Watts. A simple classification method is used to identify active status of all electronic appliances. The feature of wearable activity recognition includes two types that are used to identify dynamic and static behaviors. Their individual activity recognition models are described in this chapter. After ambient and wearable activity recognition model are described, he fusion mechanism of ambient and wearable is going to describe in detail.

**In chapter4**, the healthcare system is used to real-time aware residents’ activity based on our proposed hierarchical activity recognition model. We describe the adaptive learning mechanism of this healthcare system in detail. The framework of online mode and offline mode are also described in this chapter. The offline mode is an important role to build the first generation AR model. In the offline mode, the system collects data from environment and wearable devices, after number of days the system will train the hierarchical AR model and provide an interface for residents to label their activity. In the online mode, the system provides a real-time monitoring function and it has ability to discover unknown activity and retrain the activity recognition model. We uses case-based reasoning (CBR) algorithm to implement the function of discovery. CBR is an artificial intelligent method and the process of solving new problems based on the solutions of similar past problems.

**In chapter5**, we will show the details of the experiment environment and the evaluation metrics. The experimental results are discussed and analyzed in this chapter as well.

**In chapter 6**, we give a conclusion and discuss the future work.

# Preliminaries

## Pervasive Environment

Over the past two decades, ubiquitous and pervasive computing have been evolving[[7](#_ENREF_7), [8](#_ENREF_8)]. Users are surrounded by many different devices capable of capturing and processing information. The importance of this area has been recognized by researchers and funding bodies alike. The most common system is the Smart Home. It has been focused on developing techniques to implement a home that has ability to identify residents’ demand and automatically provide services. For example, it has ability to achieve intelligent light controls, window shutters, safety system or kitchen appliances, etc. In particular, there has been considerable interest in developing a smart healthcare home that can support for elderly or disabled residents. The goal of smart healthcare home is making it safe for them to live at their home. This approach is basically concerned with a fixed space that is require to provide intelligent features.

Beyond the fixed space of the Smart Home, the mobile user presents different and more challenging problems. The most different situation between fixed space and mobility is user’s location. The pervasive system always try to provide access to devices and services in the user’s environment. However, it is hard to control the mobile user’s environment information. The research into fixed spaces associated with buildings is generally quite independent of that being conducted on pervasive systems for mobile users. Those separated systems make the support for pervasiveness is limited. It is a challenge that controls all devices included ambient devices and mobile devices in the same system.

For our system, we have built a smart home environment at Room 313 of Barry Lam Hall (BL 313) in National Taiwan University. Although the smart home used to achieve energy saving in the before, we try to use those constructed devices to build an activity-aware healthcare home. The energy saving system of this constructed smart home is called M-CHESS. M-CHESS is the abbreviation of M2M-based Context-aware Home Energy Saving System[[9](#_ENREF_9)]. The based function of M-CHESS is aware of the surrounding contexts, e.g. the on-going users’ activities and the status of electronic appliances. However, the context structure of M-CHESS is not suitable for the robust activity-aware healthcare system, because it developed for monitoring users’ activity of using electronic appliances. In this work, we want to monitor residents’ daily living activities, so M-CHESS is hard to identify some activities which without using electronic appliances, e.g. doing exercise or cleaning home. We try to use mobile devices to monitor these kind of activities. We adopt the smart watch “Zen Watch” to monitor users’ vital sign, e.g. accelerometer and gyroscope on the smart watch. In the next chapter, we will describe the fusion method between ambient sensors and wearable sensors; that ambient sensors are the constructed devices of M-CHESS and the wearable sensors are built on Zen Watch.

The layout of the home is as shown in Fig. 2‑1. That environment specifically consists of 4 rooms, namely, living room, studying room, kitchen and bedroom. The current sensor is a simple smart meter on the embedded device “Taroko” that is used monitor the on/ off status of each electronic appliance. Moreover, each room has been equipped with temperature, lumen and humidity sensors on Taroko. 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.

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|  |
| Fig. 2‑1 The 2D ichnography of the smart home in BL 313 |

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”. First type of sensor is as shown in Fig. 2‑2(a). Second type of sensor is as shown in Fig. 2‑2(b). We will use their sensor data to build a machine learning model that uses to category residents’ activity; the detailed processing procedure will be described in chapter3.

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| --- | --- |
|  |  |
| (a) | (b) |
| Fig. ‑ The sensor deployed in the home environment | |

In order to realize specific physical activity of an elder, using the wearable sensors to collect their vital sign is necessary. Note 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 [[10](#_ENREF_10)]. 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 “Zen Watch”. It is equipped with a tri-axial accelerometer, gyroscope and low energy Blue-tooth with 30 Hz sampling rate. We have preprocessed those acceleration data of each axis to obtain mean and variance every second. Extracting orientation of pitch, roll and yaw from its accelerometer and gyroscope. Then find mean orientation and variate of orientation every second as machine learning features. Each pattern extracted from the accelerometer and gyroscope inside the wrist watch indicates a waving motion of arm, and the numbers of consecutive waving motions can be associated with a specific activity. We will use machine learning method to categorize the waving motions, and the results will serve as new features for activity recognition. The detailed processing procedure will be described in chapter3.

## Non-parametric Statistical Distribution

Nonparametric statistics are statistics that not based on parameterized families of probability distributions. Says, the typical parameters are usually the mean or variance of the distribution. For non-parametric statistics, they do not assume about the probability distributions of the variables being assessed. They include both descriptive and inferential statistics. The difference between non-parametric and parametric model is that the former will grows the number of parameters with their amount of training data; but the latter needs to give a fixed number of their parameters. The major goal of our system is reducing the burden of labeling step. The non-parametric statistic is an important role for our recognition model because it makes the recognition model not ask user assign the specific number of their daily activity. A recognition model used non-parametric statistic concept can identify activities from its amount of training data.

The term of non-parametric statistics has two different meanings. The first meaning of “non-parametric” techniques do not rely on the data belonging to any particular distribution, e.g. “distribution free” methods, which do not rely on assumptions that the data are drawn from a given probability distribution. The second meaning of “non-parametric” techniques do not assume that the structure of model is fixed. Says, the model is growing in size to accommodate the complexity of training data. And individual variables are assumed to belong to parametric distributions, and assumptions about the types of connections among variables are also made. These type of techniques include non-parametric regression and non-parametric hierarchical Bayesian models. The former refers to modeling where the structure of the relationship between variables is treated non-parametrically. The latter allows the number of latent variables to grow as necessary to fit the data. Individual variables still follow parametric distributions and the process controlling the rate of growth of latent variables follows a parametric distribution. The Dirichlet process is one of distributions in this category.

In our system, we try to detect users’ activity in real-time. For activity detection, such parameter specification may face several challenges. First, it is hard to find the appropriated parameter values for personalized models that may be different for different users. Second, for a single user, user’s behavior patterns may change over time. Given a fixed parameter is not suitable to build the inference model. In other words, the most appropriating parameter values must be adjusted accordingly. Hence, we try to achieve that the model has ability to automatically select parameter values based on individual users’ training data. Our inference activity model uses nonparametric statistic methodologies. Including the non-parametric Bayesian methods “Dirichlet process mixture model (DPMM)” and non-parametric lazy learning “k-nearest neighbor (KNN)” algorithm. The former can avoid declaring the number of activities and routines in a person’s daily life beforehand in parametric settings. The latter does not make any assumptions on the underlying data distribution.

### Dirichlet Distribution

Before we design the learning model of Dirichlet process mixture model, we need to realize the based distribution “Dirichlet”. The Dirichlet distribution is a model of how proportions vary. In other words, the Dirichlet distribution is a family of continuous multivariate probability distributions parameterized by a vector of positive reals. And the Dirichlet distribution is denoted as . 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 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 given that each event has been observed times. Dirichlet distribution is the conjugate prior distribution of multinomial distribution. There are existing the number of successes in a sequence of independent data that each data in one of *k* possible outcomes with probabilities *p1*, …, *pk*; Multinomial models the distribution of the histogram vector which indicates how many time each outcome was observed over *N* trials of experiments.

|  |  |
| --- | --- |
|  | (‑) |

Dirichlet distribution is parameterized by a vector of , where and . Define a random vector , where , and . The Dirichlet distribution with vector has a probability density function shown as follows:

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| --- | --- |
|  | (‑) |

So is mapping to the probabilities *p* of multinomial. We say that Dirichlet is the conjugate prior of multinomial. And the support of dimensional Dirichlet distribution is the dimensional probability simplex. Let , meaning that the first components have the above density and the weight of should be defined as follows:

|  |  |
| --- | --- |
|  | (‑) |

*e.g.*, a set of parameter describes a Dirichlet distribution with . When the set of concentration parameter is , the distribution of is uniform.

### Dirichlet Process

The Dirichlet process assumes dimension of the Dirichlet distribution is infinite, so the non-parametric learning model can be built based on this characteristic. The Dirichlet process is an infinite-dimensional generalization of the Dirichlet distribution and it is denoted as , where is a positive real number called the concentration parameter and 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 means the realizations are all concentrated on a single value. On the contrary, in the case where limit of means the realizations become continuous.

If a distribution is , it is a Dirichlet process.

|  |  |
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|  | (‑) |

Where and a Dirac delta function . To construct infinity sequence of mixture weight using the stick-breaking scheme, that represented as , where are sampling from the base distribution . The Dirac delta function centers on . The are defined by a recursive scheme from the beta distribution. The parameter defines how concentrated the distribution is equation (2‑5) and .

|  |  |
| --- | --- |
|  | (‑) |

In many applications, the infinite dimensional distributions appear only as an intermediary computational device. They are not required for the initial specification of prior beliefs or the statement of the final inference. The Dirichlet process is used to avoid infinite computational requirements.

## Inference Model of Machine Learning Techniques

Machine learning is a subject of computer science and it evolves from the study of artificial intelligent and pattern recognition. Machine learning explores the construction and study of algorithms that learns from and make predictions on data. The machine learning algorithms build a model that make data-driven predictions or inferences from instance inputs. Machine learning tasks are classified into three main categories, depending on the learning “signal” or “feedback” available to the learning model. Each is supervised learning, unsupervised learning and reinforcement learning. And I will briefly introduce them in the below.

Supervised learning: Given the learning algorithm a “teacher”, then the computer is presented with example inputs and their desired outputs. And the goal is to learn a general rule that maps inputs to outputs. Teacher means a set of specific labels of the training data. In other words, supervised learning analyzes the training data and produces an inferred function, which is called a classifier

Unsupervised learning: It does not necessary labels to implement the learning algorithm. Leaving it on its own to find structure in its input. Unsupervised learning is trying to find hidden structure in those unlabeled data.

Reinforcement learning: The environment is usually formulated as a Markov decision process (MDP). That the reinforcement learning does not require knowledge about the MDP and they target large MDPs where exact methods become infeasible. In other words, a program of reinforcement learning technique interacts with a dynamic environment in which it must perform a certain goal, without a teacher explicitly telling it whether it has come close to its goal or not.

In our activity-aware system, we use and modify some machine learning techniques in order to build the hierarchical activity recognition model, including two unsupervised learning algorithm, mixture model and k-nearest neighbor algorithm, and one supervised algorithm, support vector machine.

### K-Nearest Neighbors Algorithm

K nearest neighbors (KNN) is a simple unsupervised learning algorithm that stores all available cases and classifies new cases based on a similarity measure, e.g., distance functions. KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970’s as a non-parametric technique. A case is classified by a majority vote of its neighbors, with the case being assigned to the class most common amongst its K nearest neighbors measured by a distance function. If K = 1, then the case is simply assigned to the class of its nearest neighbor. Three distance functions are used to measure the similarity of each instance. They are Euclidean distance, Manhattan distance and Minkowski distance.

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It should also be noted that all three distance measures are only valid for continuous variables. In the instance of categorical variables the Hamming distance must be used. It also brings up the issue of standardization of the numerical variables between 0 and 1 when there is a mixture of numerical and categorical variables in the dataset.

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Choosing the optimal value for K is best done by first inspecting the data. In general, a large K value is more precise as it reduces the overall noise but there is no guarantee. Cross-validation is another way to retrospectively determine a good K value by using an independent dataset to validate the K value.

### Mixture Model

A mixture model is a probabilistic model for representing the presence of subpopulations within an overall population, without requiring that an observed data set should identify the sub-population to which an individual observation belongs. It corresponds to the mixture distribution that represents the probability distribution of observations in the overall population. A general mixture model, which is usually present the infinity-dimensional mixture model, is a hierarchical model consisting of the following components. *N* random variables corresponding to observations. It assumed to be distributed according to a mixture of *K* components. N corresponding random latent variables specifying the identity of the mixture component of each observation, each distributed according to a K-dimensional categorical distribution. A set of K mixture weights, each of which is a probability (a real number between 0 and 1 inclusive), all of which sum to 1. A set of K parameters, each specifying the parameter of the corresponding mixture component. In many cases, each "parameter" is actually a set of parameters. That a basic parametric mixture model can be described as follows:

In the case of Bayesian setting, the mixture weights and parameters are random variables, and prior distributions are placed over the variables. So the weights are usually viewed as a k-dimensional random vector that drawn from a Dirichlet distribution. In other words, all parameters are associated with random variables. The form of Bayesian setting shows as below. And the parameters of , , , , , , and are same to the general mixture model’s parameters.

Using and to describe arbitrary distributions over observations and parameters. That will be the conjugate prior of . And in the field of mixture model, is typically using Gaussian distribution that called Gaussian mixture model (GMM). But we will use Dirichlet process as the based distribution as , and it is called Dirichlet process mixture model (DPMM). The detail implement process will describe in the chapter3.

### Conditional Random Fields

Machine learning is about learning structure from data. And the Conditional Random Fields (CRFs) are a class of supervised machine learning algorithm. CRF is used for classification or structured prediction. Whereas a simple classifier predicts a label for a single sample without regard to "neighboring" instances, a CRF can take inputs’ pre-inputs into account. This characteristic makes CRF has ability to evolve temporal information for the inference model. And CRF is a type of discriminative undirected probabilistic graphical model. It encodes known relationships between observations and construct consistent interpretations. Although the concept of CRFs is similar to the popular machine learning algorithm “Hidden Markov Model (HMM)”, it is more powerful than HMM. CRFs are able to consider more observations from a number of pre-inputs’ data. And CRFs are often used for gesture recognition, motion recognition and activity recognition[[11](#_ENREF_11), [12](#_ENREF_12)].

We try to use Conditional Random Field to classify users’ daily activity in online mode. Before the system builds CRF, the system used unsupervised learning methodologies DPMM and KNN to build the hierarchical activity inference model of offline mode and asked user to label their activity of the processed training data that has been categories into a set of clusters by the hierarchical activity inference model. Because the training data are labeled in offline mode, the supervised learning algorithm is able to build its classification model. In order to considering features over multiple time steps, the system also automatically examine features that link state transitions in the model directly to observations.

A conditional random field may be viewed as an undirected graphical model[[13](#_ENREF_13)], globally conditioned on X, the random variable representing observation sequences. To define G = (V, E) to be an undirected graph such that there is a node v ∈ V corresponding to each of the random variables representing an element Yv of Y. If each random variable Yv obeys the Markov property with respect to G, then (Y, X) is a conditional random field. In theory the structure of graph G may be arbitrary, provided it represents the conditional independencies in the label sequences being modeled. However, when modeling sequences, the simplest and most common graph structure encountered is that in which the nodes corresponding to elements of Y form a simple first-order chain.

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| Fig. ‑ Graphical structure of a chain-structured CRFs for their sequences. |

The probability of a particular label sequence y given observation sequence x to be a normalized product of potential functions.

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The transition is a feature function of the entire observation sequence and the labels at positions and in the label sequence; is a state feature function of the label at position and the observation sequence; the parameters and are used to estimated training data.

A set of real-valued features of the observation to expresses some characteristic of the empirical distribution of the training data that should also hold of the model distribution. Each feature function takes on the value of one of these real-valued observation features, if the current state or previous and current states take on particular values. The detail implementation of CRF will describe in the chapter3.

# Activity Recognition Model by Ambient and Vital Sign Fusion

## The Architecture of Activity Recognition Model

In order to real-time monitor elderly residents’ daily activity, we are necessary to design an activity recognition model. I have propose an activity-aware healthcare system that has two modes for utilizing: training mode and online mode. The training mode is used to identify activities from data automatically as a number of clusters. Each cluster presents a meaningful activity. The system will ask user to label each cluster as one activity. After all clusters are labeled, the online model will use those labeled data to build an inference model by conditional random field.

The goal of offline mode is trying to identify all observed environmental and wearable sensor data as living activities in the offline mode. And reduce the burden of labeling those observed sensor data. The system categories sensor data as a set of clusters by the non-parametric hierarchical activity recognition model (NHARM). User only needs to label each clusters, so the number of labeling data is decreasing.

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| Fig. ‑ Flowchart of Training Mode |

To monitor elders’ living activities, but it’s hard to ask them labeling their activities for every instances in training section. Because the offline mode can find the significant living activity of each cluster, it help elders label the result clusters in the easy way. Besides, the advantages of NHARM is not only an easier way to label data, but also a way to observe data and category them automatically. Non-parametric learning method can find the most appropriate number of clusters based on their training data. For NHARM, it is a set of data-driven and non-parametric inference models, it may discover some facts which are ignored by users, *i.e.*, user usually remembers significant activities, but ignores common/normal activities. The ordinary activity recognition methods are using supervised learning algorithm, and they need to label all training data. When user ignore those common activities and label them into false activities, those wrong labeling data will become noise data for those supervised learning models. And they will show bad performances in prediction stage. Although one activity may not map to one cluster from our NHARM, one cluster only map to one activity. *i.e.*, one activity can map to one or more than one activity, and one cluster should map only one activity. When users labels clusters, they can label different clusters as same activity. For example, if one has two habits of reading books: open lamp or close lamp, the NHARM identifies two clusters for this reading behavior and both of them should be labeled as the same activity “Reading”. The Fig. 3‑1 shows the flowchart of training mode.

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| Fig. ‑ Flowchart of Online Mode |

The online mode is used to real-time determine activity of elderly residents and monitor anomaly activity. If an unknown activity has been observed, the system will determine whether it is an anomaly activity or not. The procedure of determining anomaly activity is used an artificial intelligent methodology “case-based reasoning (CBR)”. Case-based reasoning solves new problems by adapting previously successful solution to similar problems. So before we design CBR in our activity-aware healthcare system, we need to design a function to compute the similar score of all known activity. This function can evaluate any new instance how it is similar to all observed activities. And we set a threshold *T* that is used to determine the instance is belong to the most similar activity or an unknown activity. If the highest similar score is still lower than threshold *T*, the system will consider this instance is a new activity (or called a new problem). Then, the CBR mechanism will be triggered. If this unknown activity is similar to an anomaly activity, the system will send an alert message to the elderly resident’s caregiver. After the system provide service that sent an alert message or do nothing, it will require resident to label this activity and retrain the AR model of online mode. The Fig. 3‑2 shows the flowchart of training mode.

In the chapter3, I will detail describe the algorithms and implementations of AR model of both training and online mode. And the architecture of the activity-aware healthcare system will describe in the chapter4, such as the labeling interface for training mode or the mechanism of CBR for online mode.

## Activity Recognition Model of Training Mode

The AR model of training mode has two main layer. For the first layer, we propose two separated AR models for ambient and vital sign parts, so they can identity activity individually by their training data. For the second layer, before we fuse the results from the first layer, transforming vital sign part to has the characteristic of event-trigger format. The system considers the clusters of vital sign part from the first layer as new features. *i.e.*, each cluster is considered as a sensor, so the number of clusters means the number of dimension for new features. And each activity can map to specific clusters. This characteristic is similar to ambient part. For example, the activity “watching TV” of ambient part can be determined by the “On” states of TV and living light. Says, the activity is observed by the characteristic of event-trigger. For the part of vital sign model, when user watches TV and the AR model of vital sign part determines a cluster, the cluster is considered as a sensor which used to monitor user’s activity of “watching TV”. When the system determines a result of this cluster, the system can infer an activity “watching TV” occurred. The characteristic of both ambient part and vital sign part are similar, so they can fuse in an easier way.

### Activity Recognition Model of Ambient Part

Before building the AR model, extracting feature is an important part. In machine learning, feature extraction starts from an initial set of measured data and builds derived values intended to be informative, facilitating the subsequent learning. The ambient sensor data is extract as Boolean variable: on and off, because they are triggered by human activity, *e.g.* current sensor on Television measures low power when Television is close; but measuring high power when Television is open. The types of ambient sensor contain current sensor, lumen sensor and switch sensor. The state of each sensor is training in the development stage. The feature of current sensor presents the active status of its attaching electronic appliance is “On” or “Off”. When a current sensor attaches on one electronic appliance, we will record its current data in close status. And computing mean and standard deviation of the recording data. A threshold is used to determine the active status of the electronic appliance is “On” or “Off” by its current sensor data. The Threshold is . If a value of input sensor data is higher than , the activity status of its appliance is “On”; otherwise it is “Off”. The feature extracts from lumen sensor is likely to current sensor. And the switch sensor will response on and off, so we do not need to preprocess the data of switch sensors.

The system collects ambient sensor data every 5 seconds as training data for a numbers of day. And using k-nearest neighbor (KNN) algorithm builds the activity recognition model of ambient part. We need to decide cluster heads of the activity recognition model. Because

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