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利用粒子群最佳化演算法於智慧電網社區  
電力需求管理

Power Demand Side Management Using   
Particle Swarm Optimization in Smart Grid Community

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1. 中文摘要

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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

## Related Work

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](#_ENREF_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](#_ENREF_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.



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

## Objective

## System Overview

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