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真實環境中基於人為中心之情境感知年長者健康照護系統

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真實環境中基於人為中心之情境感知年長者健康照護系統(初稿)

Human-centric and Context-aware Pervasive Healthcare System in the Hospital for Elderly People

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中文摘要

隨著老年人口的快速增加，越來越多國家逐漸重視老年福利政策的實行。然而，在健康照護人口不足的情況下，要讓每位年長者得到足夠的服務是困難的。為減輕社會人力與資源上在老年健康照護上的負擔，我們提出一個非侵入式且結合多模感測器偵測年者長狀態之情境感知健康照護系統。藉由自動的偵測年長者行為並監測長時間的行為改變，照護者就算無法隨伺在年長者身邊仍能掌握他們的健康狀態。本論文之特色在於，不同於以往大部分進行健康照護的研究，除了在資訊工程理論上的探討，跨領域的結合包含質性研究的分析亦被納入考量。為求讓所提出的照護系統能真正符合使用者需求以及適合被放入真實環境中。

本論文之貢獻主要有三項：首先，真實環境(本論文中為台大醫院 9A、9C 護理站)的需求分析為跨領域研究帶來目標與困難的收集。其中，針對醫院工作者在現況中遇到的困難，我們提出可能解決的辦法。此外，由於在醫院中進行情境感知是非常困難的。直至目前，台灣僅少數研究達成在醫院中進行情境感知相關的研究。如何在醫院中進行包含感測器佈建與行為辨識，亦為本論文之貢獻之一。最後，基於行為辨識結果所採取的應用目前已有一套雛型。雖然由於場地限制還未有年長者實地使用，經由實地訪談後，由年長者本身所提出的珍貴意見亦成為我們提供服務的改進方向與指標。本研究為多模感測器進行情境感知應用於醫院中的里程碑。我們期待如此科技與醫療的結合不但能提供醫療照護者與年長者有用的幫助，更能激發跨領域工作者基於本研究提供的寶貴意見。

關鍵字：普及健康照護, 情境感知, 行為辨識, 多模感測器結合。

Abstract

Due to the rapid growth of the aging population, numerous countries have been attaching importance to establishing the well-being of the elderly. However, shortage of qualified caregivers makes it difficult to serve prompt care to elderly people. To alleviate the possible social costs associated with manpower and physical resources, we propose a context-aware healthcare system which makes use of multi-modal and un-obtrusive sensing technology meanwhile taking human feeling into account. By inconspicuously and automatically monitor the health status of the elderly, caregivers can get hold of the behavior changes even the elderly is not under caregivers' supervision. Distinctively, rather than focusing on technological research purely, we take multidiscipline ideas into account to make our healthcare system more human-centric and practical in use.

The main contribution of this thesis is three-fold. Firstly, we conduct need survey in National Taiwan University Hospital and summarize the difficulties and expectations of healthcare workers which can be used as the goal of healthcare assistance system. Secondly, strategies and core ideas to put pervasive sensors into real-world will be present. Thirdly, since we have designed a series of applications using persuasive technologies. Although elderly people have not yet been recruited to do user tests, many suggestions from interviews can be regarded as the guidelines of researchers in healthcare.

Keyword: Pervasive healthcare, real-world healthcare, context-aware, situation awareness, multi-modal sensor fusion

Relevant Publications

Parts of contributions have been published in two conference papers. More details regarding the following two chapters can be found in the listed papers respectively:

1. *Yu-Chun Yen*, Jiun-Yi Li, Ching-Hu Lu, Tsung-Han Yang and Li-Chen Fu, “Human-Centric Situational Awareness in the Bedroom," 9th International Conference on Smart Homes and Health Telematics (ICOST), 2011

2. *Yu-Chun Yen* , Ching-Hu Lu, Yi-Chung Cheng, Jing-Siang Chen, and Li-Chen Fu, " Towards an Evidence-Based and Context-Aware Elderly Caring System Using Persuasive Engagement," 14th International Conference on Human-Computer Interaction (HCII), 2011.

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Chapter 1

Introduction

1.1 Motivation

Aging population is becoming a critical global issue. Huang *et al.* report that approximately 10 percent of the world's population is over the age of 60, and the proportion will be doubled by 2050 [28]. In 2010, United Nations for Human Rights pointed out that the aging population has become an international issue. As a result, an increasing number of countries have recognized the importance of establishing the well-being for the elderly. To alleviate the possible social costs of lacking manpower and physical resources, it is necessary to develop assistive technology to help elderly people live independently.

Activity of daily living (ADL) is one of the most important information when performing elder care services. Traditionally, daily living of the elders are reported either by periodical interviews of caregivers or self-reported by elderly patients, which tends to be subjective and error-prone. However, the medical staffs have no choice but trust these unreliable reports, since there is no other source for obtaining ADL. Such a problem obstructs the medical staffs from knowing the real situation about the elderly. By enabling the autonomous detection and analysis of elders ADLs, a substantial amount of burden of caregivers can be reduced. As a result, many researchers pay attention on developing autonomous monitoring and analysis system to assist elderly people and caregivers. This motivates us to design an evidence-based report system that collects and analyze ADLs of elderly autonomously.

Most of current works focus on technology aspects and do not deal with real-world challenges such as sensor deployment and gathering user requirement on-site. On the contrary, this work pays more attention to develop a practical healthcare system. Specifically, we focus on devising the real-world deployment techniques based on empirical experiments as well as understanding user requirements through field studies on geriatrics. For example, we have conducted interviews with several domain experts in both National Taipei University of Nursing and Health Science, and Department of Psychology in Fu Jen Catholic University. Also, this research involves a multidiscipline teamwork with medical staffs and psychologists. As a result, a human-centric pervasive healthcare system is designed based on the research findings mentioned above.

This research can be regarded as the milestone of the practical pervasive healthcare system research in Taiwan especially for a real-world hospital environment. Future studies in this field can benefit from this work by reusing the research outcomes, the infrastructure, and empirical experiences presented in this thesis.

1.2 Challenges

Bricon-Souf *et al.* have pointed out the importance of pervasive healthcare systems by enumerating a number of research topics such as “healthcare”, “ubiquitous”, and “pervasive” [32]. Although considerable works have been dedicated in developing healthcare systems, most of them are still prototypes in laboratory, and thus only focusing on technological aspects rather than the healthcare domain. As reported by Alemdar [33] and Bricon-Souf [32], the transformation from prototypes to practical healthcare system is still a challenging task, which will be elaborated below.

- **Challenges of Activity Recognition in Healthcare Research**

ADLs are critical for medical staffs to diagnose or to predict the possible illness of the elders. Considerable research has been performed to devise mechanisms for recognizing activities based on different assumptions. Often, the first thing to do is to obtain data from appropriate sensors. After that, the sensed data are analyzed to infer what activities have been performed.

Hence, two issues should be addressed when developing activity recognition systems. First, both technological and social aspects should be considered since the system is mostly placed in a private space such as home and hospital. Generally speaking, sensor deployment can be divided into two categories: intrusive and non-intrusive. From the technological view points, wearable sensors such as RFID or accelerometer are known as intrusive sensors. Sensors in pervasive environment such as pressure sensors or light sensors are categorized in non-intrusive sensors since the residents can perform daily activities without noticing the sensors. Although wearable sensors are capable of gathering and providing data in a direct way, however, they have to be attached to human body all the time and thus are infeasible for practical uses. From the social’s view point, the intrusive sensors refer to the sensors that are capable to provide rich information such as camera and high-resolution microphone. These

Table 1-1 Healthcare system in real-world environment

Project Name	Proposer	Context Information	Setting
Pervasive Healthcare Project(Denmark)[6][7]	E.Bardram *et al* University of Aarhus	**Activity features** Location, status(self-report status), scheduled activity **Resident features** Patient ID, professional ID/role **Environment features** Medication, location artifacts	RFID , Hospital PDA
Context-aware mobile communication in hospital	J. Favela *et al* University of Aarhus,CICESE	**Activity features** Artifacts status **Resident features** Participants involve in activity **Environment features** Location timing, artifact location	Handheld recorder, printer, screen, mobility PDA, weight sensor
Follow Me video Application in Accident & Emergency Department	S. Mitchell *et al* University of Cambridge	**Activity features** Decisions about task for medic staff **Resident features** Professional ID **Environment features** Location timing, artifact location	Hospital active badge, micro speaker, video touch sensitive screen

sensors are mostly violating the privacy issues of the residents. As a result, how to choose appropriate sensors that provide sufficient information while being non-intrusive is nontrivial and therefore a challenging task.

Besides, how to choose the appropriate models for classifying human activities is also a challenging task. Since non-intrusive pervasive sensors can only detect the interactions between human and the items in the environment. Uncertainties should be taken into account when inferring activities.

- **Challenges of applying context-aware in real-world environment**

To infer activities using non-obtrusive approach, sufficient context information have to be gathered from sensors However, there are few sensors that are suitable for real environments, and the features extracted from these sensors are often simple. Table 1-1 lists the characteristic of project running in the hospitals. More detailed description about each project will be presented in Section1.3.3. Table 1-1 reveals that majority of these projects focused on detecting the medical staffs activities rather than patients. One possible reason can be the deficiency of sensor modalities that limits the ability to obtain sufficient data information from patients. Rich sensors such as cameras or voice recorders are usually not feasible in real-world deployment. For those living in the real environment, they are not willing to be recorded all of time to learn their behavior. In addition, it is hard to perform data annotation. As a result, alternative ways to make the model evolve should be devised.

- **Challenges of acceptance of new technology**

There might be gaps between system developers and other people who are indifference even afraid of new technology. How to establish consensus with those people is important. For medical staffs, it is necessary to acquire agreement on system achievements from them since they are the front line persons to meet the elderly people. Benefits in medical field brought by our system are the most important consideration. For the elderly patients, how to let them trust the system is the key. The privacy issue and safety considerations are mostly concerned by elderly people and their caregivers.

1.3 Related Work

1.3.1 Activity Recognition

In literature survey, researches have investigated considerable approaches to recognize human behaviors in healthcare field. Human detection in room is a hot topic for its usage in both surveillance system and fall detection for healthcare [44]. However, most of such human detection researches employ vision-based camera which may violate the privacy of the residents seriously. Some other researches utilized wearable sensors such as RFID tag or accelerometer sensors to monitor human presence. Bardram J *et al* [6] asked medical staffs wearing the RFID card and they put RFID reader in pervasive environment. Although it can be used to collect information about whom and where the residents taking what artifact in environment, it is inconvenient for residents since they have to do more actions than their ordinary life.

Regarded as an utmost situations that is concerned by both caregivers and clinicians numerous researches. Bathroom activities monitoring is a trend in activity recognition field. J. Chen [43] proposed an acoustics bathroom monitoring system, they collected sound data and then extracted MFCC feature. Parameters of Hidden Markov Model are carefully designed by those extracted features. Although they addressed the privacy concerns, they look upon the optimistic aspect which was not the reality in real-world environment.

Several researches have proposed non-obtrusive methods to detect bed-related situations using pressure sensor array. A. Arcelus *et al* analyzed the sit-to-stand timing from 132 bed pressure sensors which are uniformly distributed on bed. Sensor output form sequences of pressure images. Region of interested (ROI) detection algorithm was designed to extract regional signals from the hips and the hands. They claimed that the unobtrusive nature of their detection approach makes them suitable for continuous monitoring system in smart home environment [15]. The high recognition rates show the promising of their system to detect the bed-departure time. However, they disregarded the location of pressure sensor and instead considering the total variance of pressure readings on bed. It makes their algorithm non-appropriate to detect other situations performed on the bed. I. Veledar *et al* modified their methods by adding floor pressure array beside the bed. They aimed to reduce the computing complexity of algorithm proposed by A. Arcelus[15]. Centre of pressure (COP) is calculated for each pressure image and they regarded the movement of COP as the starting time of sit-to-stand situation. Although their methods performed well in detecting sit-to-stand situation, the additional floor pressure sensor array is not suitable to be deployed in existing environment [16].

To monitor different postures on bed, C.C. Hsia *et al* analyzed pressure sensitive bed and compare different sleeping posture. They used Kurtosis and Skewness estimation approach to represent the shape of the pressure distribution. Principal component analysis (PCA) then transformed complex data set into salient spatial features which cannot be observed directly. Finally, they injected those features into

Figure 1-1 Different Sleeping Postures to be classified[17]

SVMs to classify sleeping posture [17][18]. However, they didn't consider the temporal transform of on-bed situations so that they can only monitor the sleeping posture at a particular time. Moreover, they only classify lateral posture (shown in Figure 1-1). C.J. Hou *et al* aimed at analyzing the variance of pressure distribution within different behaviors of bed-ridden elderly people. They deployed 20 pressure straps and calculate the Activity Score proposed by Mori [20] to observe the variance of activity score. Although they have observed the variance of activity score within different activities, they just show the variance of activity score rather than classifying different behaviors.

1.3.2 Healthcare System Proto-types

The aging population has gained much attention by considerable researchers. Several assisted healthcare system have been proposed from various research groups. Georgia Tech established a prototype home, called AwareHome, to create a living laboratory for interdisciplinary research using ubiquitous computing [39]. They focused on human-centered research which involved a special application in supporting for the elderly. It combines context-aware, ubiquitous sensing, computer-vision and acoustic tracking technologies. Another living laboratory PlaceLab project, which is part of the House_n projects are supported by Massachusetts Institute of Technology (MIT), TIAX, and LLC [40]. In their work, hundred some sensors have been embedded into their living lab which used to capture audio-visual activities including information about objects manipulated, environmental conditions, and use of appliances.

Focusing on medical healthcare, the University of Washington's Assisted Cognition project [41] incorporates with their Medical Center and Alzheimer's Disease Research Center to explore the usage of AI system in supporting independence and life quality of Alzheimer's patients. They adopted sensors such as infrared based active badges, GPS, Berkeley motes, and accelerometers to do location tracking which helps reduce spatial disorientation both inside and outside the home. Other sensors such as weight sensors (on beds and furniture) and current monitors are utilized to help patients carry out multi-step everyday tasks.

University of Virginia is working on AlarmNet[30] which is an assisted living and residential monitoring network aiming to achieve a pervasive adaptive healthcare with diverse need. Their prior work, called the SATIRE[31], has been integrated into the AlarmNet project that utilizing accelerometer data from wearable sensors to do activities recognition based on Hidden Markov Model. In the AlarmNet project, they additionally adopt physiological sensors and emplaced sensors to access rich data about the patient. Rather than inferring ongoing activities, the emplaced sensors were used to illustrate the environmental quality and to support location information using motion and tripwire sensor. They did online analysis on sensor data and designed a user interface shown the circadian activity rhythm (CAR) of a patient.

1.3.3 Real-world Healthcare Systems

Much more challenges emerge only when system moving out of the controlled lab. To our knowledge, only few of the pervasive context-aware healthcare system have been deployed into a real-world environment outside the computer science laboratory. Table 1-1 briefly lists three renowned projects. In this section, description about each work will be introduced here.

J. E. Bardram [6] proposed the design principles for applying context-aware computing in hospital and further shared the experiences from real-world deployment of context-aware technologies in a hospital environment [37][7]. They have arranged three categories deployment issues involving hardware, software, and user setting which can be used to evaluation our system [38] In their work, although they have deployed their system into real-world environment, they focused on observing the status and location of the medic staffs rather than taking care the status of the elderly people. The contexts they extracted are location, self-report status, and scheduled activities. Feedbacks from the users mentioned that it was tedious to self-report own status and to use RFID tag since they have to approach the RFID reader.

J. Favela *et al* conducted ethnographic informed design to support context-aware collaboration in a hospital [34] They claimed that hospital work is the management of large amounts of information which are highly dependent on contextual information such as location, role, time of day, and activity. To better understand how information exchanging between medical staff and to design the way to give assistance for hospital worker, they conducted 196h workplace study and gathered context information by handheld recorder. They represented collected data in format and fed all the recorded data into Hidden Markov Models and Neural Network [35]. After that, they compare the result between the two method and expert observers. The expert observers are conducted by *human test* that test how the medical teams estimate activities from contextual data. Result showed both machine learning methods outperformed the expert observers. Therefore, they were excited in transferring location aware computing to activity-aware computing in the hospital. Although the result looks promising, they ignored the automatic context detection in real-world environment which is the most difficult problem.

M. Tentori *et al* further impose application in hospital [36]. They used weight sensor attached on the urine bag. Whenever the patient doing such activities, the weight sensor will be triggered and wirelessly transmit the condition of the patient to the nurse through smart phone. The nurse can consult the activity description by pressing the button on the screen.

1.4 System Framework

As mentioned earlier, knowing ADLs plays an important role in elderly healthcare. Traditionally, daily living reports are obtained from periodical interviews and manually recorded reports/data obtained by caregivers or self-reported by elderly patients. Sugar *et al.* reported that there may be significant differences between patient assessments and performance-based measurements of ADL functioning in hospitalized elderly at time of discharge [42]. Without objective evidences from other sources, medical statffs have to completely trust the subjective reports. It becomes worse in the hospital since every nurse takes responsibility to more than ten elderly patients in average. This motivates us to design a *daily living report system* to automatically collect and analyze activity data of elderly patients. In addition, we also design a virtual caregiver which can perform timely remind and encourage elderly people. The actions and reminders of the virtual caregiver are metaphor of the caring behaviors of a human caregiver.

The conceptual framework of the proposed system is shown in Figure 1-2 The proposed evidence-based and continuous health improving framework. The main objectives are providing *evidence-based daily living report* for the caregivers and persuading the elderly people achieve more active lives. The inhabitants interacting with the ambient intelligence (AmI) enhanced environment are not only the source of sensor data but also receivers of care services.

In the *Evidence Collector* module, since user's ADLs can be used to infer health related status. For instance, an abnormal living pattern may reveal some physical or mental problems. The *Evidence collector* collects each daily living clue of the inhabitant. It gathers information by various ways such as automatic recording technology from the sensed environment or in-time observation from a caregiver. After acquiring evidence of daily living information, the *Context-aware analyzer* outputs meaningful features based on the collected information. Some living problem may appear after further analyzing those features. The *Persuasive engagement* gives prompt assistance or encouragement whenever the *Context-aware analyzer* brings out interested situations. Ascribing to the appropriate intervention of *Persuasive engagement*, we expect the improvement in

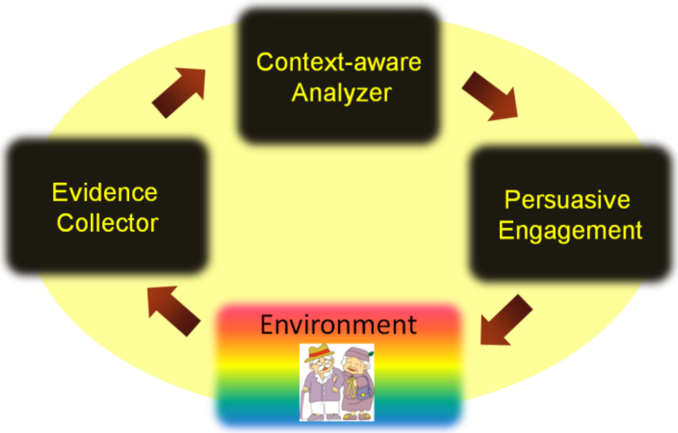


Figure 1-2 The proposed evidence-based and continuous health improving framework

health condition. If the inhabitant follows the suggestions and services supported by *Persuasive engagement*, the changing living pattern will be perceived by *Context-aware analyzer* since it continually analyzes evidence coming from *Evidence collector*. In the end, the *Persuasive engagement* will appropriately interact with the inhabitant according to his/her ameliorating health condition.

1.5 Objectives

Based on the above discussions, the overall objective of this thesis is to achieve a human-centric pervasive healthcare system, which includes the following items:

- **Non-intrusive sensing technology and multimodal classification**

  To non-intrusively monitor diverse situations of the elderly patients and their caregivers, intrusive sensors are away from our pervasive environment. Sensor data from the residents are all unconsciously detected by ambient sensors. Moreover, to capture diverse of situations, multimodal classifiers are incorporating to take charge of corresponding monitoring task.

- **Sensor management and loosely coupled platform design strategy**

  Multimodal sensors and various classifiers adopting will lead us think about coupling problem. To make proposed system more flexible and robust, loosely coupled fashion is adopted to isolate each monitoring task and sensor from others. The loosely couple design will make the whole system remain stable even if one or some monitoring tasks are under modifying or increase the potential to add-in or remove-out sensors or classifiers from systems without affecting unnecessary element in system .

- **Offline cross-subjects of system evaluation**

  To deal with the difficulty of labeling in real-world environment, we conducted several real-world experiments to cross-test the proposed system. By various testing from different people, system will learn the uncertainty between different objects.

- **Bring the bridges of computer science research and medical needs**

  To impose expert knowledge and get agreement from medical staffs, we run several cross-domain meetings and iteratively prototype our system design aiming to take real-world considerations into account. Moreover, to understand true needs of our target users, ethnography approach is conducted from system design to evaluations. In addition, we explain system goals to target users in technology-free way to make them understand and trust in proposed system.

1.6 Thesis Organization

The rest of this thesis is organized as follows. In Chapter 2, to make our monitoring targets meet the needs for caregivers, we conduct workplace studies and systemize the user requirement in this chapter. Chapter 3 illustrates several sensor deployment policies, how to develop a context-aware environment while taking human feeling into account will be addressed here. Data preprocessing and feature extraction approaches are also explained in this chapter. Chapter 4 describes the procedure of doing situation awareness task based on received features. Issues about how to establish a multi-agents system are discussed in the chapter. In addition, for each monitoring agent, the idea and the constructing way of corresponding inference engine will be illustrated here. In Chapter 5, the experiment settings are introduces, and the evaluations of the proposed system are shown in this chapter. Finally, Chapter 6 summarizes the whole thesis and lists the future work.

Chapter 2

Field Study

Understanding and characterizing the nature of human activities is of critical importance for a pervasive healthcare system[3]. Ethnography method of inquiry is a popular qualitative research method that has been adopted extensively in information systems design[2][4]. Various approaches can be used to gather empirical information about human societies and cultures such as participant observation, interviews, and questionnaires [10]. In our work, we have conducted several expert interviews to improve the design of our system. Moreover, we performed field studies in National Taiwan University Hospital by investigating the needs of both elderly people and caregivers. Before conducting the experiments in the hospital, we discussed with medical staffs. In addition, we also applied for the Human Subject Research Ethics Committee / Institution Review Board (IRB). After getting the accepted certificate from IRB, we then start conducting the experiments in the hospital.

The field study is carried out in the 9C ward of National Taiwan University Hospital. Patients in 9C are mostly before or after received treatments related to digestive diseases. We explained our observation objectives to the lead medical staff of

9C ward. First we observe two experienced nurses when they conduct ward round. In the process of study, we apply similar structured observations approaches and semi-structured interviews to consolidate understanding of caregiver and elderly patient behaviors. Structured observation has been proposed to produce more robust understandings of the dynamics of human activities. Researchers in structured observation are allowed to study individual episodes in a comprehensive way [2]. Totally five complete working shifts of the nurses are observed and documented. After obtaining detailed information of how nurses interact with elderly people, we adopt semi-structured interviews to complement and clarify our observation results. Some elderly patients are interested in our work and are willing to give advices to us.

2.1 On-Site Structured Observation

We utilized paper-and-pen works to record what we have observed in the five working shifts mentioned above. After establishing the nurse working shift lifecycle, we discuss with the nurses and probe the difficulties they have faced based on each process of their nursing work. Next, we proposed a list of potential assistances for the medic staff and ask for their advices. All results provide helpful insight of designing a pervasive healthcare system.

Figure 2-2 shows the complete nurse working shift lifecycle. We define one complete shift begins in shift changing from previous working shift and end up after the shift changing to the next shift. The doctor treatment behaviors for the elderly people is ignored since we focus on the interaction between nurses and elderly people for the reason that the person who will interact and spend more time with the elderly people is nurse rather than doctor. Then, the occurred activities, used artifacts, and participants involved are recorded. After that, we systematically present the nurse shift lifecycle diagrammatically.

The first task for one nurse shift is the patient conditions passing from previous duty nurse to the next nurse who will take over the patient in the next working shift. This process elapses about 30 minutes in average for each nurse. Information passed between successive nurse shifts is mostly related to medical information such as contents or quantities of intravenous drip, medicines the patients have taken, or the appropriate food type for the patients. We observed that they seldom pass information about physical recovery level such as whether the patients getting out of bed and taking a walk or what activities the patients have done in previous nurse shift. We also realize the reason why it is difficult to access physical recovery data is the limitation of building structure and the insufficient time of the nurses. The floor map for 9C ward is shown in Figure 2-1 and it reveals the impossibility for the nurses to access in-room living data for each patients. However, the physical recovery information regarded as some important indicator of recovery condition or estimation of recovery speed. It becomes one challenge for the nurses to know the physical condition of elderly patient. After exchanging the patient information, the duty nurses prepare necessary medical materials in the nursing center based on exchanged data. This process takes about 20 minutes for each nurse.

The major task of one nurse working shift is the ward round. After exchanging the information from previous duty nurse and preparing all stuffs for the patients, the nurse starts to run ward round from the nearest nursing room. For each nurse in 9C ward, they take charge of thirteen patients in average during one working shift. We observed that for each patient visiting, all the process can be generalized segmented into three stages which are pre-caring, on-caring, and post-caring stages. For convenience, we describe each stage of ward round in separate sections as follows.

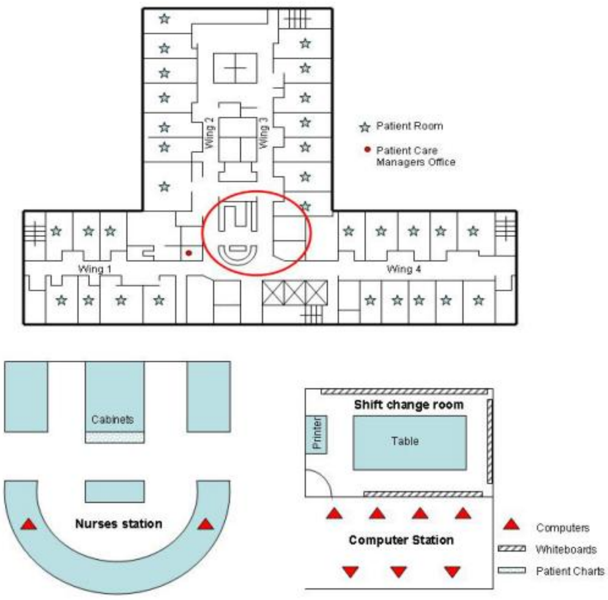


Figure 2-1 Floor map of ward 9C in National Taiwan University Hospital

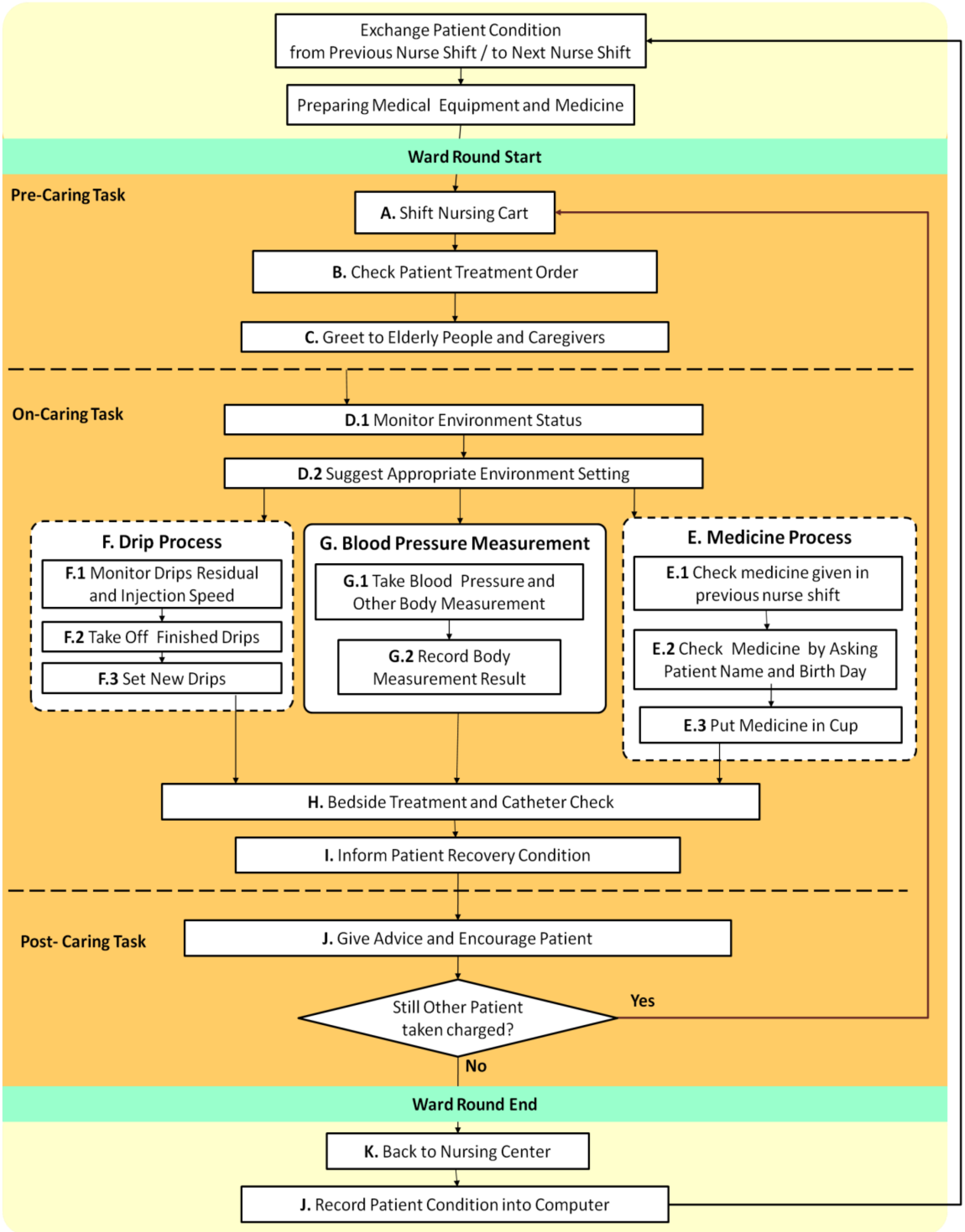


Figure 2-2 Nurse Working Shift Lifecycle

2.1.1 Pre-Caring

Before entering a particular nursing room, the nurse will push the nursing cart toward the target nursing room and stop their cart outside the door. Stuffs on their nursing cart include a laptop, paper note, pen, and medical materials such as pills, swab, or other things. They check handmade medical advice from doctors and handover data from previous duty nurse for the patient first and then push the cart into the nursing room.

For each elderly patient, the visiting nurse will firstly confirm the name and the age of the patient by oral asking. For those patients who cannot describe themselves clearly, nurses will check their bracelet containing personal information. Next, nurses will greet with the elderly people and their caregivers. We observed that nurses often remember status of not only the elderly people but the caregivers. For instance, nurses will actively ask the caregivers they have occurred recently and care the follow-up. This makes the relationship between nurses and elderly patients much closer. We have found out that the more the nurses closer to the caregivers, the more the caregivers and elderly people trust in the nurses or medical staff. In addition, we found that the atmosphere will be changed according to the social interactions in the nursing room. The residents who turn on and watch TV will make the atmosphere in the nursing room become cheerful. Moreover, if the caregivers chat with the elderly patient when they are lonely will makes the elderly people very joyful.

2.1.2 On-Caring and Post-Caring Stage

After the warm greetings, nurses will monitor the environment status of the nursing room such as the air conditioner temperature. From our observation, it happens very often that the nurses have to adjust the air conditioner when they visit the elderly patients. It indicates that the caregivers may not be conscious of bad environment status. After adjusting and suggesting the better way of environment status, the nurses start to do the main nursing task involving injecting/extraction of drip process, blood pressure measurement, and giving prescribed medicine. We have found that although the nurses teach every caregiver about how to stop the drips, caregivers are always very nervous when the drips are ready to be exhausted. Things will happen that the caregivers will continuously press emergency call or directly come up to interrupt the nurses even when she/he is working on another patient.

For the blood pressure measurement, nurses have to record the measured data into the laptop by themselves. After measuring the blood pressure, the nurses will report the result for the elderly people and inform them whether they are under good condition. From our viewpoint, it will be tedious for the nurses to key in the measured data since they have to transfer their position from the bed-side to the nursing cart. For some patients who are just back from operation, nurses will ask their pain level using standard 10-level pain indicator.

To supply prescribed medicine, nurses will give a little cup containing all the medicine pill the elderly patient has to take. To remind the correct taking time, nurses will record the time on the cup and ask the caregivers to remind elderly people taking medicine on time. However, there are still some patients forget having medicine in the right time. It might extend the recovery time since the next prescribed medicine may not be taken on time.

After the entire monitoring task, the nurses will check the recovery status and the wound carefully. The nurses will then inform the estimated time of discharge from hospital to the elderly patient and caregivers. Before they leave the nursing room, the nurses will encourage the elderly people trying hard to leaving bed as more as possible.

2.2 On-Site Semi-Structured Interview

After conducting on-site structured observation, we listed important items that appear to be important indicators for the recovery of the elderly people. Some of them are proposed by the nurses themselves. We confirmed our observations with the two nurses and then adjusted the system goals to meet the expectation of caregivers. The following items are important physical indicators to estimate the elderly people condition mentioned above.

- **The leaving bed frequency**

  The frequency of leaving bed in a period time for the elderly patient

- **The times of toileting**

  The frequency of toileting in a period time for the elderly patient

- **Status of the caregivers around the bed**

  Whether the caregiver is accompanying with the elderly people

- **Food/Water intake**

  What food the elderly people intake and water quantities they have drank.

- **Medicine taken status**

  The time stamp of taking medicine

- **Environment status**

  The environment status that includes light degree, temperature, and humidity degree of the environment

- **Activity level of elderly people**

  How much physical activities the elderly people have performed.

The items 1-3 listed above are referred by the nurses as *the leaving bed frequency*, *Status of the caregivers around the bed*, and *Medicine taken status*. Both the two nurses expect to know how many times the elderly people leaving from bed. They have mentioned that some patients don't like to try their best to getting out of the bed. It will raise the possibility to get bedsores and the wound might be ulcerating if their body remains in an inactive condition. In addition, they also care about whether the caregivers are accompanying the elderly people. Ordinary, they ask caregivers to inform the nursing center whenever they leave the nursing room. One of the nurses has experienced bad situations that the elderly people were falling down when the caregivers are leaving nursing room.

2.3 Summary

Based on the analysis of observations and interviews presented in previous sections, several important features of a human-centric pervasive healthcare system can be identified:

- **Social Engagement Evaluation**

In the Pre-Caring stage, we decide to evaluate the social engagement using ambient sensors. The reason to detect the social engagement is to acquire estimated mental health status of the elderly people. Many approaches can be adopted to evaluate the social engagement such as interviews or field observations. Among these approaches, we believe that ambient sensors will be the best way to evaluate the social engagement. Social engagement happens in anytime so that it is impossible for the nurses to observe elderly people all the time. Moreover, privacy concerns related to the content of social engagement such as the channel of TV or the chatting contents have to be considered seriously. Therefore, it is not appropriate to use camera or high-resolution microphone to monitor these situations. It follows that the ambient sensors is more suitable for monitoring the social engagement.

- **Bed-side Contexts Monitoring**

According to the results of both observations and interviews, the bed-side contexts are difficult to be aware by the caregivers. For example, it is important to turn the elderly patient’s body over periodically to prevent bedsore. Current approach to record the turning time in the NTUH is to manually record. It turns out to be a burden for the caregivers. Therefore, it is helpful to automatically record the turning body time stamp for the elderly people. In addition, to monitor whether the elderly people is ready to leaving bed is also helpful for the nurses since they expect to know the leaving bed event in abnormal condition such as under low illumination or under unsupervised situations. As one of the nurses mentioned, low illuminations can cause accidents in a room so that it is also necessary to detect lighting condition. The time of leaving bed can also be used to evaluate the recovery speed or estimate the body condition. Various approaches have conducted to monitor the bed-related situations for the elderly people. To acquire more detailed information such as turning the body, previous works have adopted wearable sensors[46]. However, for the elderly people, it is not suitable for them to wear additional sensors and it might be disturbance for the elderly people when they taking rest.

- **Unsupervised Situation Monitoring**

Both of the two nurses expect to be promptly informed whenever the caregivers are not in the nursing room. It motivates us to automatically detect whether the elderly patient is under unsupervised.

- **Bathroom Situation Monitoring**

The toileting frequency is one of the indicators that can tell the digestion recovery status. It is hard for elderly people to remember when and frequency of toileting. Moreover, risks may happen when the elderly people go to the bathroom alone. Therefore, we set this issue as a goal of our system, which automatically detects the situation in the bathroom and record the frequency of toileting.

Chapter 3

Collecting Data in the Pervasive Healthcare Environment

To gather information in the pervasive healthcare environment, we build a wireless sensor network containing non-intrusive ambient sensors such as pressure sensors, current sensors, motion sensor, light sensors, sound sensors, and humidity sensors. The data gathered by these sensors are useful for analyzing human behaviors or interactions between human and daily objects. We also use a wired laser range finder (LRF) to detect human locations.

In a real-world pervasive healthcare environment, many human-related deployment considerations should be taken into account. For instance, the sensors must be carefully deployed so that they bring least disturbance to residents' daily lives. Based on our experiences, we find that there are some principles and guidelines for sensor deployment, which will be reported in Section 3.1.Next, in order to detect the user situations listed in section 2.3 , we analyze each of them and then consider practical issues of deploying ambient sensors. Note that since we exclude intrusive sensors, e.g.

wearable sensors and vision-based sensors, it will be more difficult to infer these user situations since we cannot obtain rich sensor information. For clarity, we explain sensor deployment for each situation category separately in Section 3.1. Next, the pre-processing procedures of sensor data will be presented in Section 3.2. Finally, discussions of lessons learned from our real-world sensor deployment experiences will be addressed in Section 3.3.

3.1 Sensor Selection and Deployment Policies

In order to gather context information of residents in the pervasive healthcare environment, we deploy ambient sensors in the nursing room by iteratively prototyping and discussing with various domain knowledge experts. First, the most relevant sensors are selected to detect meaningful events that we are interested which will occur in the pervasive healthcare environment. In the following, we list all of the deployed sensors and describe their sensor readings.

- **Light, Humidity, and Temperature sensors(**Figure 3-1 **(a))**

  The light sensors provide the light information of the environment. The ranging of provided light level information is from 0 to 4095. The bigger value represents the brighter light level of the corresponding area. The light sensor is adopted to monitor whether one area is under low illumination condition. The information coming from humidity and temperature sensor tells the humid degree and temperature of corresponding area. For some disease such as influenza is highly correlated to the variance of humidity or temperature change. Moreover, the humidity and temperature sensors can indirectly provide evidence of some situations such as taking a shower. The sensor reading range of both humidity and temperature are 0-4095 and range respectively.

- **Pressure sensor (as shown in** Figure 3-1**(b))**

  The value of pressure sensor reading indicates the degree of external force pressing on a particular place. Therefore, According to the reading of pressure sensors, we can indirectly estimate the posture of the elderly patient since the pressure readings will be different when performing different postures on bed.

- **Motion sensor (as shown in** Figure 3-1 **(c))**

  The motion sensors provide information about whether there are human beings moving in a specific area. In our work, we exclude vision-based or wearable sensor to detect the movement of the human being. The motion sensor is an alternative approach that can detect human movement in a non-invasive way.

- **Current sensor (as shown in** Figure 3-1 **(d))**

  The current sensors are adopted to detect the state of the electric appliance mounted on. Some of situations can be estimated by knowing the states of electric appliance; therefore, the state of interested electric appliance is monitored.

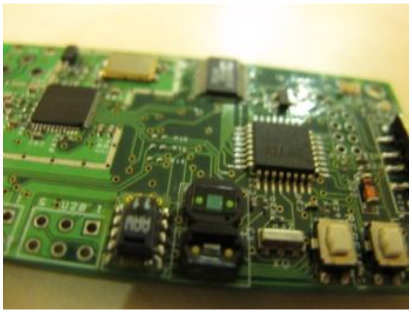
- **Sound wave sensor (as shown in** Figure 3-1 **(e))**

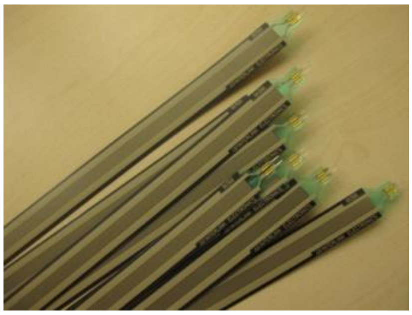
  The sound wave sensor detects whether there is sound uttered in the environment. To protect the privacy issue, the sound sensor we adopted in our work is very low-resolution. Rather than recording the sound data, we only detect the intensity of sound occurring in the environment. The content of speaking is noninvertible since any detected sound has been very distortion comparing to original sound.

- Laser Range Finder (LRF) **(as shown in** Figure 3-1**0 (f))**

The LRF sensor gathers coordination sets of all obstacles in at a particular time. Based on the observed result, we can analyze whether the interested objects appearing in the environment. For example, it can be used to detect whether there is human being in the specified area.

For convenience, we introduce our sensor deployment policies separately


(a)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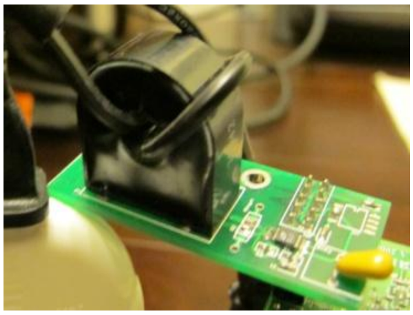

(d)


(e)


(f)

Figure 3-1 Sensors (a) light sensor, humidity sensor, temperature sensor, (b) pressure sensors, (c) motion sensor, (d) current sensor, (e) (Left) sound sensor, (f) LRF sensor according to different monitoring purpose listed in section 2.3.

3.1.1 Bed-side Monitoring Sensor Deployment

To monitor the situation of the elderly people on the bed, we use several pressure straps and put them on the bed top to measure the variance of pressure distribution. Whenever the elderly people stay on the bed, the pressure distribution of several pressure sensors will change with his/her posture.

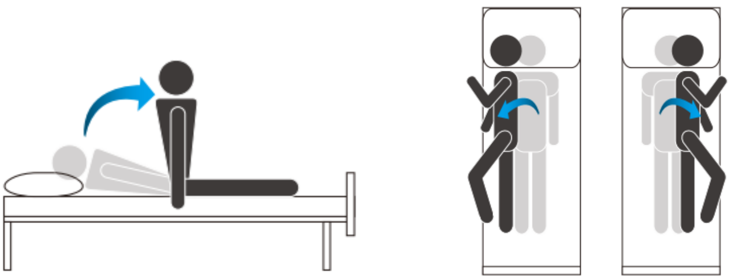
Based on our observation, the bed might be shifted from one room to another one. It will be troublesome for the medic staffs if we attach our pressure sensors on the bed permanently. Therefore, to make our pressure mat portable, we add another layer between the nursing bed and pressure sensors. All the pressure sensors are attached on the additional layer which we called pressure mattress hereafter. Therefore, if the caregiver wants to clean the bed sheet or move the bed, they can easily take away the pressure mattress on the bed and put it back after cleaning the bed sheet.

In addition, to receive pressure sensor readings that are sensitive to body movement, the position to put the pressure mattress should be taken into consideration. M. Holtzman *et al.* have examined outputs from sensors placed below a variety of mattress types and compared the response to outputs from sensors placed on top of the mattress [8]. The experiment result shows that the sensor outputs will be much more sensitive to body movement when putting pressure sensors on the bed top rather than under the bed. Therefore, we put our pressure mat on the bed mattress. Moreover, to bring least mental distraction, we hide our pressure mat below additional bed sheets as Figure 3-4(c).

(a) (b)

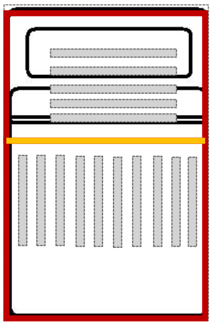
Figure 3-2 The deformable character of nursing bed. (a) The deformed nursing bed. (b) The flat nursing bed structure.

Various sensor arrangements have been made for prototyping our pressure mattress. There is one real-world deployment challenge that has been ignored by other pressure mattress researches, the deformable characteristic of the nursing bed. Based on our observational field study, the headboard of the nursing bed is most likely to be lifted off in daytime which is shown in Figure 3-2(a). The nursing bed will keep flat (as picture Figure 3-2(b)) only when the elderly people is taking rest or just coming back from operation. Such deformation will raise the probability of sensor damage and incorrect sensor reading especially for those sensors deploying near the folder line. To strike the



(a) (b)

Figure 3-3 (a) Lengthwise body movement (b) Lateral body movement

(a) (b)

(c)

Figure 3-4 (a) Layout of our pressure straps attaching on the pressure.

(b) The pressure sensors deployment in the real environment

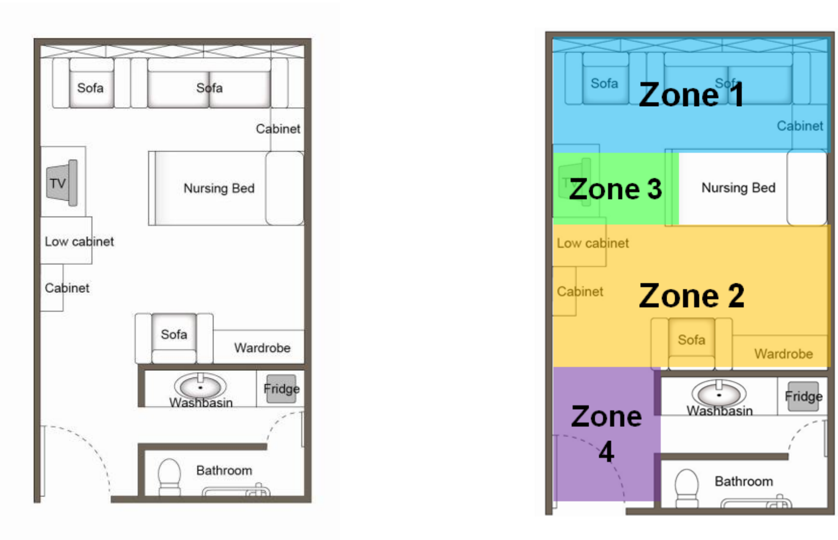
(c) The complete pressure mattress deployed on the bed top.

challenge, we conceptually segment the pressure mat into two parts as Figure 3-4(a) and avoid to putting sensors on the folder line which is colored yellow. There are two manners of body movements involving lateral and lengthwise movement shown in Figure 3-3. The lengthwise body movements often consist of upper body movements. To monitor this kind of movement, we deploy the pressure mat in horizontally parallel way that can distinguish whether the head and the shoulder parts of the elderly people are lying on the bed. For the lateral body movements, sensors deployed in the lower region are adopted in vertically parallel distribution that can distinguish the gravity shift from center to left or to right side of the bed.

3.1.2 Caregiver Leaving Monitoring Sensors

To monitor unsupervised situation, we detect whether there are caregivers appearing in active zones. We define active zones as the rectangle areas that the caregivers can take care to the elderly patients if they are in these zones. Figure 3-5(b) shows the active zones in our pervasive environment. Figure 3-5 reveals that nursing bed and bathroom are not active zones for the reason that we assume caregivers will not be on bed; and the caregivers cannot take care of the elderly patient when they are in the bathroom.

Considerable ways have been adopted to monitor human beings in specified areas. W. Huang *et al* employed the camera to detect the situation around the bed [9]. Despite the visual system can obtain rich information on human postures, the involved



(a) (b)

Figure 3-5 (a) The layout of our experimental environment. (b) Active zones in our experiment environment.

computational complexity is high and its performance is varied with the camera settings as well as the environment (such as different view-angles of the camera and different illuminations). Based on our observational result, activities performed in the nursing room are under low illumination when the elderly people are taking rest. Such environment will render the camera become less preferable. Moreover, the privacy violation of camera might be a critical concern for an elder or a patient.

To make the residents living in their ordinary ways, we also avoid asking them wearing wearable sensors such as accelerometers or RFIDs (Radio Frequency Identifications). Therefore, we choose sensors which can detect human body in the specified area. The status of caregivers in the environment can be simply categorized into active and non-active. For each active zone, we deploy sensors to detect active and non-active body status. Motion sensors are sensitive to body movements, so they are appropriate to monitor active status for human beings. However, caregivers may be in non-active situation when they sit while chatting or watching TV in the environment. LRF sensors are chosen to compensate these situations. The LRF sensors will run the

(a) (b)

Figure 3-6 Sensor deployment for unsupervised situation monitoring.

(a) LRF sensor beneath the bed (b) Motion sensors of different active zones.

human detection algorithm which proposed by Chen *et al* to detect whether there are human legs in the environment [14]

To minimize the sensor usage, we deploy our sensors on purpose. Figure 3-6 (a) shows that we place the LRF sensor under the nursing bed so that we need only one non-active human detector in our environment. Figure 3-6 (b) reveals that we employ two motion sensors to detect each active zone since the two active zones are segmented by the nursing bed.

3.1.3 Social Engagement Sensors

Various indoor social engagements can be inferred based on ambient sensor data. We categorized social-related situations into two types. One is pure social interaction between human beings without using any objects. Sensors adopted to detect this kind of interactions are mostly environment sensors such as sound sensors or motion sensors. The other type of social engagements involves appliance or instruments usage such as

(a) (b)

Figure 3-7 Sensor deployment for social engagement monitoring.

(a) Current sensor attached to the television. (b) Light, humidity, temperature and sound sensor in the front of the bed television or telephone. To detect this kind of social interactions, we attach sensors such as current sensors or accelerometers on the appliance or instrument. In our pervasive healthcare environment, we detect both types of social engagement which are chatting and TV watching respectively. The total time of doing these two social engagements are used for estimating mental condition of the elderly people.

Current sensors are easy to measure total time of electronic appliances in use. Therefore, we mount the current sensors to the television to monitor the total watching time. Figure 3-7(a) represents the way we connecting the original power line of television to the current sensor. And to monitor the chatting time, we adopt the low-resolution sound wave sensors to detect whether there is potential human sound in the nursing room. The sound sensor is attaching to one board and the board will then be plastered on the wall. For the sake of gathering up sensors in the same place rather than placing in scattered way, we attach the sound sensors on the same board

3.1.4 Bathroom Monitoring Sensors

The major activities performed in the bathroom are toileting and taking a shower. To monitor the bathroom situations, various considerations should be taken into account. Risks especially tripping may happen after the elderly people enter the bathroom. Although there are many vision-based or wearable sensor based fall detection researches [11],[12], it is impossible to put vision-based sensors in the bathroom since it will severely violate the privacy issue. Also, it is not appropriate for the elderly people to wear wearable sensors when they enter the bathroom since it might become a disturbance. Therefore, we depend on the ambient sensors to estimate the activities performed by residents.

(a)

(b)

Figure 3-8 The sensor deployment for the bathroom situation monitoring.

(a) Motion sensors in the entering zone. (b) Light, Humidity, Temperature and sound sensors

The light, humidity, and temperature sensor readings can be significantly different in different situations. For example, the humidity and temperature sensor readings will be much higher than ordinary if the resident is taking a shower. Therefore, we adopt these sensors in the bathroom. The flushing and speaking situations will introduce different sound patterns that can be distinguished by our low-resolution sound sensor. Note that our sound sensor doesn't violate the privacy issue for the residents. Unlike previous works that adopting high-resolution microphone so that had the ability to

Figure 3-9 The entering zone that is monitored by a motion sensor

distinguish detailed situation. Our sound sensors only detect the voice intensity and the result will be fused with ambient environment sensor states to do further inference.

In addition to monitor environment status in the bathroom, the entering zone in front of the bathroom door is of critical importance. It served as recorder of starting and finishing time of the bathroom situations. Risks happened in the bathroom cannot be monitored by ambient sensors. The entering zone sensor will detect the abnormal situations in the bathroom if the elderly people entering the bathroom but never going out for a period time. To monitor the entering zone, we employ one motion sensors toward the bathroom door as Figure 3-8(a). It will be triggered whenever there is human being entering into or coming out from the bathroom.

3.2 Pre-Processing of Sensor Data

An evidence is a monitored interaction between a human and devices in a pervasive healthcare environment. As indicated in the previous section, all selected sensors are simple ambient sensors and thus are non-obtrusive. Meanwhile, a situation is a human task that the resident is currently performing. The relationship between a situation and its corresponding sensors values are dynamic. Before inferring situations, the sensor data are pre-processed by a sequence of procedures that make raw data easier to be handled by the context and situation recognizers introduced in the next chapter. Since the purpose and characteristic of each sensor is quite different, each type of sensor data has to be pre-processed in a different way.

3.2.1 Quantization

After receiving the sensor data, these data will be quantized into several states. Each sensor value is quantized by comparing with a corresponding threshold that is pre-determined based on the properties of the sensors. After the quantization step, the sensor values can be transformed into a sensor state. Before the quantization procedure begins, one has to define the states for each type of sensors such as whether the television is in used and whether there is body movement in a specified area.

3.2.2 Data Fusion

To estimate bed-related contexts, all pressure sensor readings are fused to represent the pressure distribution of the pressed area. In other words, a pressure vector of the pressure sensors is defined. Hence, the area of each pressure sensor represents meaningful location information.

3.2.3 Feature Extraction

Depending on the characteristics of a sensor type, different feature type representation is defined for different type of sensors. Table 3-1 shows a list of different sensor types and their corresponding feature types.

Table 3-1 Feature extracted from each type of sensor

Sensor type	**Preprocessing**	**Feature type**	**Description**
Pressure sensors	Data fusion	Numeric vector	The pressure distribution of bed pressure mattress
Current sensors	Quantization	Binary	The states of TV {On, Off}
Laser Range Finder	Human Detection Algorithm[14]	Numeric	Number of human in a particular active zone.
Motion sensor	Quantization	Binary	Whether there exists human movement in a particular active zone. {On, Off}
Light sensor	None	Numeric	The light illumination in a particular space
Humi ity sensor	None	Numeric	The humidity degree of a particular space
Temperature	None	Numeric	The temperature of a particular space (°C)

3.3 Discussions

Valuable lessons and experiences have been acquired from our deployment process in real-world environment. Each of the lessons should be kept in mind in any multidiscipline research especially when the computer science connecting to other field which is unfamiliar with engineering. It is not enough to do analyze user requirement but the observation of system design cost time consume as well. Much more practical challenges and issues will be emerged only when we face to the real-world environment. Challenges includes either the deployment difficulties and target users recruitment. We list them down below and explain our experiences.

- **Establishing the strong connection throughout system establishment**

  The connection between the engineering researchers and the medic staffs such as nurses, doctors, and psychologist should be strongly connected throughout the research. Opinions interflowed within inter-cross meeting should involve **system goals**, **deployment policies**, **collaboration ways of multidiscipline experts**, and **experiment process flow**. We began to hold monthly meeting with medic staffs and psychology experts when system is under establishing stage. Significant and precious viewpoints that ignored by engineers may be proposed from those domain experts who directly face elderly people. For example, we ignore the importance of monitoring whether the elderly people be turned over in the period time. Another case is that the medic staffs drop the labeling ground truth procedure in real-world environment. Although annotating data is an important procedure in machine learning, it is too intrusive to make the elderly patients and their caregivers willing to join our research.

Moreover, since patients mostly trust in their attending physician, the best way of gaining the trust of our research from elderly people is to obtain the identification of our system from the medic staffs. Clearly statements of medical achievements rather than engineering terms should be illustrated. Only when the medic staffs agree with the potential benefits of our system will render them feel confident of persuading and explaining our system to real elderly patient.

- **The limitation of deploying time**

Since we implement our system in the real hospital environment, the big challenge is the high rate of room occupancy. To least disturb the ordinary process in the hospital; we apply limited time for deploying our sensors. The first procedure is to **measure the layout** of the nursing room and **decide the power supply** place for each sensor. Although taking pictures of nursing room cannot help in providing correct distance between sensor and corresponding power sockets, it speeds up the time for deployment design since we have little chance to directly observe the nursing room.

In deployment stage, how to **hide the sensors** in the environment is important. Lu *et al.* classifies deployed sensors into seamless and seamful categories which take residents' ergonomic concerns into account. They suggest taking advantage of as many seamless devices as possible especially for an ambient intelligence environment [13]. In our sensor deployment, we remain as less as exposing sensors in the environment. We try to let the nursing room keep on the original appearance.

After setting up all of the sensors, the **sensor and network robustness** should be examined. We run our system in the pervasive healthcare environment for about two days since we have no more days to test our system. Notice that some of the sensors which are connecting to a series of USB lines may not work well due to the power decrease. These sensors should be checked carefully.

Chapter 4

Context-aware Situation Awareness in Pervasive Healthcare System

To build up a pervasive healthcare system, several issues should be carefully considered to make the whole system suitable to monitor various situations in a real-world environment. The following are the key problems to be resolved when the proposed system is going to be deployed in the hospital, which is the test bed of our 1st generation pervasive healthcare system.

- Sensor Data Management

The issue about sensor data management in the real-world environment is the live status of sensor condition. In the proposed healthcare system, a heartbeat from each sensor will be sent to the base station in every period of time. Therefore, to monitor the live status of each sensor, an agent is designed to continuously monitor the heartbeat from each sensor. If a sensor stops to send the heartbeat, the sensor is most likely dead. In addition, to easily check the correctness of the sensor reading, a monitoring interface is designed to help the system developer understand sensor reading at certain time in a precise way. Therefore, in this way it will be easy to check the properness of the deployed sensors quickly so as meet the challenge which is lack of enough time for the checking process.

- Adopting of Multi-modal Situation Recognizer

In a pervasive healthcare system, it is not appropriate to use a single type classifier to monitor the overall situations. The reason is that, for each situation, characteristics of, say, sensor adopted and human behaviors may be significantly different. For example, in order to let temporal relationship to smooth out the state changes for situations involving successive behaviors, models which take the temporal transition into account should be adopted here to monitor this type of situations. For some situations, a decision making only regards the status at a certain specific time rather than over a sequence of state changes. A decision tree or other approaches may be more appropriate to model this kind of situations. Therefore, to better monitor the overall situations, taking advantages of different classification approaches and incorporating heterogeneous classifier to monitor situations at a particular time will be suitable for handling the entire monitoring task.

- Loosely coupled inference platform

To modify or adjust a single situation, the preferable way is to let the classifier be isolated from other situation classifiers so that the other classifier will not be affected (i.e. no need for retraining) if the target classifiers are under testing phase. Additional advantage of loosely coupled platform is the flexibility to add or to remove classifiers.

- Remote Data Access

To least disturb the residents living in the pervasive environment; it is not suitable to enter the room several times during research time. Therefore, a remote access way to obtain data is necessary. In our pervasive healthcare environment, we record sensing data on the File Transfer Protocol (FTP) and access the data file remotely rather than do it locally within the nursing room.

An Message Queue is adopted to receive heterogeneous sensor readings. For each base station, an agent is employed to monitor every sensor under the charge of this base station. A centralized processor receives all the sensor reading and then preprocesses the data to extract the associated features. All the extracted features will be poured into the feature pool that can be accessed by every monitoring agent.

Each monitoring agent will work independently in the system based on its own characteristic features and classifier. First, the characteristic features will be subscribed by one or more monitoring agents. Based on the received features, each monitoring agent starts to infer the current situation independently. The recognized situation of one monitoring agent is defined as a basic situation. The basic multimodal situation can be further incorporated to infer high-level situations. For example, the bed monitoring agent concludes a lying-on-bed situation while the bathroom agent is trying to monitor the flushing situation. A higher-level situation such as “The caregiver rather than the elderly person is flushing in the bathroom” will be concluded. Figure 4-1 shows the overview of the proposed situation-aware healthcare system.

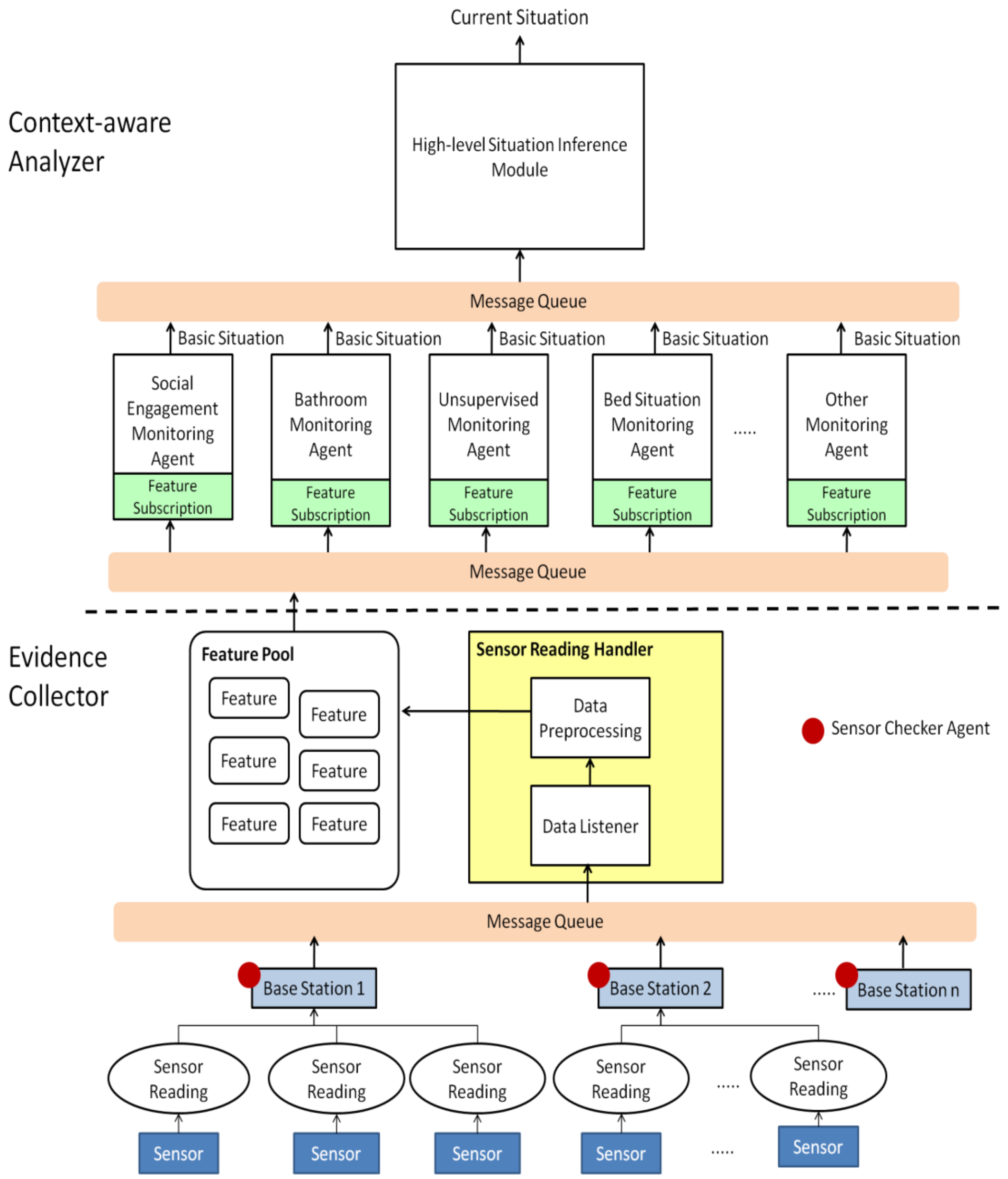


Figure 4-1 Framework of our healthcare situation monitoring system

4.1 Bed Situation Monitoring Agent

To monitor bed-related situation, feature subscribed from feature pool is only pressure vector and the basic situations will be bed-related activities of the elderly people. In addition, bed-departure situation will also be detected by analyzing bed pressure vector. Bed-related situations are used to document the health and mobility of the elderly people. In order to clarify our target monitored bed-related situation, we list interested bed-related situations as follows:

- Lying on bed
- Sitting on bed
- Leaving bed from the left/right side
- Turning the body over left/right

4.1.1 K-means Cluster Filtering

The pressure value may slightly changes when people lying on the bed, these slightly change may be falsely classified as different posture. To improve the recognition rate while reducing the uncertainty, all received vectors will be projected into clusters in order to aggregate similar samples into single cluster.

Given a training sample set $\mathbf{T} = \{\mathbf{t}_i \mid \mathbf{t}_i \in \Re_{15}, i = 1,..., N\}$. Each $\mathbf{t}_t$ is the processed vector coming *k*-means classifier We incrementally test different number of clusters and choose the best number to analyze our training data set **T**. Let the number of clusters be *k*, K-means clustering method aims to partition all training data into *k* sets $\mathbf{S} = \{S_1, S_2, ..., S_k\}$ that minimizes the within-cluster sum of squares (WCSS).

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{t}_j \in S_i} \left\| \mathbf{t}_j - \mu_i \right\|^2$$

To build the K-means classifier, two steps are alternatively processed involving Assignment and Update Centers steps. The details of both two steps are illustrated as follows:

Assignment step:

For each 15-dimension training sample $\mathbf{t}_j$ at time *t*, the distances between the sample point and each clustering centers at time *t* are calculate using Euclidean distance.

$$\arg\min_{i} \left\{ \left\| \mathbf{t}_j - \mathbf{m}_i^t \right\| \right\} \qquad i = 0,1,\ldots k$$

The sample point will be clustered as set *i* if the distance from center *i* is shortest among all other centers.

Update step:

After clustering a new sample point into cluster *i*, the new means of cluster i is refined.

$$m_i^{t+1} = \frac{1}{|S_i^t|} \sum_{\mathbf{t}_j \in S_i^t} \mathbf{t}_j \qquad \mathbf{t}_j \in \Re_{15}$$

4.1.2 Hidden Markov Model

Rather than considering on-bed posture at a particular time, temporal relationships between posture changes are modeled by Hidden Markov Model. Hidden Markov models are especially suitable for recognizing temporal patterns such as human speech or hand gestures. The transition from one posture to the next is a Markov process since the upcoming posture state depends only on current state and the fix probabilities based on observing the past behaviors. A general Hidden Markov Model is represented in Figure 4-2.

The way to represent a single posture has been proposed by using K-means clustering. Therefore, the possible observation set **V** for the Hidden Markov Model is:

$$\mathbf{V} = \{0,1,...,K-1\}$$

Where K is the number of posture clusters results from K-means clustering. Suppose $\mathbf{z}_t$ is the pressure vector observed at time t. K-means clustering sequentially process the sample vector and then output a cluster ID for corresponding point. Observations sequence of clustering IDs are denoted as $\{y(0), y(1),..., y(T-1)\}$ where T is the length of observation sequence.

$$y(t) = Kmean(\mathbf{z}_t)$$

Then $y(t) \in \mathbf{V}$ for $t = 0,...T-1$. Assume there are N states in Hidden Markov Model, therefore $\mathbf{Q} = \{q_0, q_1,..., q_N\}$ and $x(t) \in \mathbf{Q}$ for $t = 0,1,...T-1$.

The transition probabilities table and observation probability matrix are defined as

- $\mathbf{M}_{N\times N} = \{ m_{ij} \mid m_{ij} = P\left(x(t+1) = q_j \mid x(t) = q_i\right) \}$

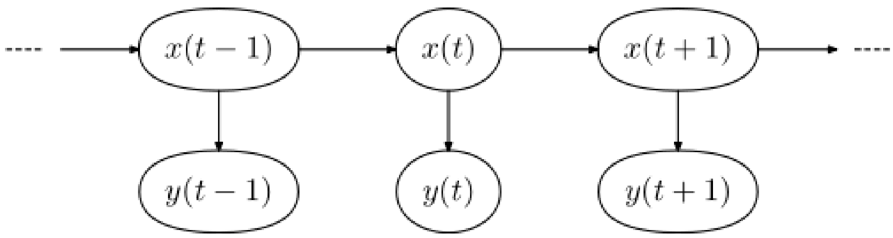


Figure 4-2 Hidden Markov Model[26]

- $\mathbf{A}_{N\times K}=\left\{a_j(k)\,|\,a_j(k)=P\left(y(t)=k\right)|\,x(t)=q_j\right\}$

Both the **M** and **A** are row stochastic. To establish a HMM model, the initial state probability distribution π is necessary. Therefore, the HMM is defined by $\lambda=(M,A,\pi)$.

For each interested bed-area situation, we establish one independent HMM. Therefore, six HMMs are incorporating to classify received observation sequence. Given models $\lambda_s=(M_s,A_s,\pi_s), s=0,1,...6$ (standing for each situation) and a sequence of observations O, the inferred situation at time *t* is determined by considering the highest likelihood of observation sequence *O* among given six models.

$$s(t)=\arg\max_{S}\left\{P(O\,|\,\lambda_s)\right\}$$

The likelihood is obtained by following equations:

$$\begin{aligned}P(O\,|\,\lambda_s)&=\sum_X P(O,X\,|\,\lambda_s)\\&=\sum_X P(O\,|\,X,\lambda_s)P(X\,|\,\lambda_s)\\&=\sum_X \pi^s_{x_0}a^s_{x_0}\left(y(0)\right)m^s_{x_0,x_1}a^s_{x_1}\left(y(1)\right)\cdots m^s_{x_{T-2},x_{T-1}}a^s_{x_{T-1}}\left(y(T-1)\right)\end{aligned}$$

To resolve the problem in a feasible way, we apply the forward algorithm to calculate the probabilities which is proposed by Stamp *et al.* [25].

4.2 Caregiver Unsupervised Monitoring Agent

To monitor whether there exist caregivers in the nursing room, we have proposed active zone as hot spots of location unit for human detecting. The result for each active zone will aggregate to decide the final unsupervised condition in the nursing room. Different detecting purpose may influence the active zones selected to be monitored. For those elderly people who are not willing to be active, active zones may be extended to a larger areas since the chance of elderly movements are little. But for those who are active, the active zones might be closer to the nursing bed since it has high probability that the elderly people may leave bed by themselves.

Assume there are k selected active zones in one space, the $HumanExist_i$ is the Boolean variable representing the existence of human being in active zone i where $0 \le i \le k$. The result of $HumanExist_i$ for active zone i is determined by a finite state machine (FSM_i) (shown in Figure 4-3). A FSM is a mathematical abstraction representing a behavior model composed of a finite number of states, transitions between those states, and actions. It is similar to a flow graph illustrating how the state transits when a particular condition occurred.

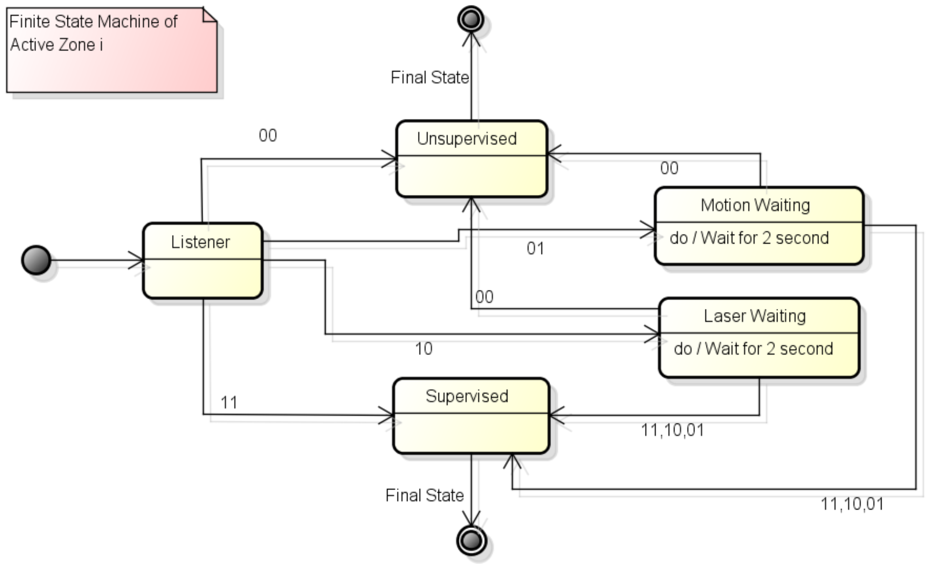


Figure 4-3 Finite State Machine of active zone

Following defines our deterministic FSM for each active zone. The FSM is a quintuple $\left(\sum, \mathbf{S}, s_0, \delta, \mathbf{F}\right)$ where:

- $\sum = \left\{ ab \mid a \in \left\{ 1 = Motion_{on}, 0 = Motion_{off} \right\}, b : \left\{ 1 = Laser > 0, 0 = Laser = 0 \right\} \right\}$
- $\mathbf{S} = \left\{ State_{unsupervised}, State_{supervised}, State_{Listener}, State_{MonitorWaiting}, State_{LaserWaiting} \right\}$
- $s_0 = State_{Listener}$: initial state of the finite state machine
- $\delta : \mathbf{S} \times \sum \rightarrow \mathbf{S}$,the transition table of FSM_i
- $\mathbf{F} = \left\{ State_{unsupervised}, State_{supervised} \right\}$

$HumanExist_i$ will be *true* whenever the output state is. Similarly, it will be interpreted as false if the FSM stops at $State_{unsupervised}$. A logic expression represents the final decision of unsupervised condition of one nursing room (Equation 4.1).

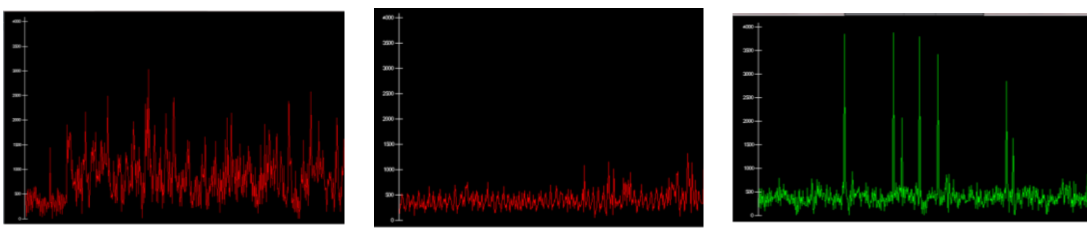
The expression reveals that we regard every active zone the same and any of the active zones i triggered the $HumanExist_i$ as *true* will violate the unsupervised condition which means there exist at least one caregiver in all active zone.

$$Unsupervised_t = \neg HumanExist_{1_t} \wedge \neg HumanExist_{2_t} \wedge \ldots \wedge \neg HumanExist_{k_t} \qquad (4.1)$$

The extension of considering the number of caregivers and the location priorities may be taken into account in the future works.

4.3 Social Engagement Monitoring Agent

Experience shows that the most commonly performed social-related activities are watching TV and chatting in the nursing room. The general audio event can be regarded as time-sequence signal. Therefore, a statistical analysis on temporal sound intensity is adopted to classify whether a conversational activity is being performed in a particular space or not. Several pilot studies have been adopted to collect the patterns of conversational events between residents. The threshold value T of the aforementioned event is determined by analyzing the average sound intensity. Besides concerning the individual sound intensity, the sequence of sound patterns are also aggregated to reason whether a conversational event is actually under way.



(a) (b) (c)

Figure 4-4 Sound intensity distribution of (a) Conversation, (b) Watching TV, (c) Sudden sound event

Assume $\mathbf{s}$ is a set of sound samples received within a time window. The $SpeakingRatio(\mathbf{s})$ will be calculated as the ratio of high-intensity sound samples within time window. If the ratio exceeds ε, which is determined in experiments, the time window will be regarded as talking activity.

$$Conversation(\mathbf{s}) = \begin{cases} 1, SpeakingRatio(\mathbf{s}) > \varepsilon \\ 0, othersise \end{cases} \tag{4.2}$$

$$SpeakingRatio(\mathbf{s}) = \frac{\text{\#Magnitudes of Sound samples exceeds threshlod value T}}{\text{\#Sound samples in window time}} \tag{4.3}$$

To detect the watching TV event, we analyze the current flow reading of the TV appliance. Since the current flow changes patterns for both turn-on and turn-off are mostly steady even at different times, it is easy to detect the watching TV activity based on monitoring of the current state. A threshold value is set to serve as the base value for determining the TV state.

4.4 Bathroom Monitoring Agent

To recognize situations in the bathroom, we take sequential features into account since getting into bathroom consisting of sequential actions. We define a state change of a sensor as an *event*. Therefore, sequential features capture the temporal information among successive events. A pair of two successive events will be encoded into one kind of sequential feature. In our research, domain knowledge is incorporated to extract relevant sequential feature.

As mentioned in Section 3.1.4, we employ a sensor to monitor human crossing the gate zone of the bathroom. Therefore, if a resident is going to the bathroom, he/she will initially trigger the motion sensor installed on the ceiling above the gate zone. However,

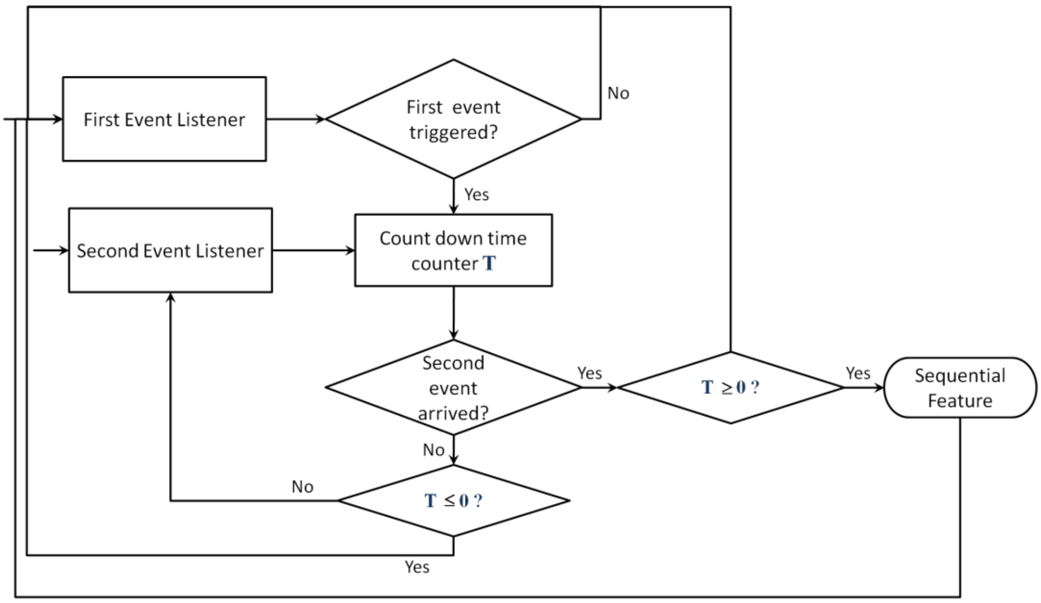


Figure 4-5 Decision flow for detecting starting time of entering into the bathroom

there still exists an uncertainty about whether he/she will enter the bathroom actually. Instead, he/she might just stay in the gate zone and wash hands. To resolve this uncertainty, we monitor the sequential feature rather than individual feature as described earlier.

A turning-on-light action is most likely to take place in the bathroom if the resident really goes into the bathroom. Therefore, we fuse the motion feature and the light feature to determine start time of the bathroom situation. The process of sequential feature is shown in Figure 4-5, where we regard motion feature as the event one trigger whereas light sensor as the event two trigger. Whenever a motion feature is triggered as $\{On\}$, event one is kicked off and the counter will set **T** seconds for the lasting time. The value of **T** is determined through several experiments. In our start time determination, **T** is set to 10 seconds since the maximum time of getting into the bathroom from the gate zone is about 10 seconds in our preliminary experiments. If the light sensor reading changes from low lumen to high lumen, event two will be regarded as being triggered. Note that the time of introducing the sequential feature in fact represents the start time of the bathroom situation. If no sequential feature is introduced within a predefined window time, the counter will reset and the handler will wait for the next event one. Similarly, to determine the end time of the bathroom situation, we take change of the light sensor reading from high lumen to low reading that below predefined threshold as event one, and the $\{On\}$ event of motion sensor will contrarily be regarded as event two.

After determining the start time of the bathroom situation, multi-modal features are cooperating to classify the on-going situations. Temperature and humidity sensor readings changed accordingly with different situations in the bathroom. In addition, the patterns of sound intensity generated by different situations are also different. To monitor situations taking place in the bathroom, we thus analyze every sensor reading in the bathroom for each situation.

4.4.1 Decision Tree Learning

Decision tree learning [21] is a common approach adopted in statistics, data mining and machine learning. It creates a tree-like graphical model to predict the value of a target variable based on input observations. The advantages of the decision tree classifiers among other data mining approach are that they are simple to understand and to interpret. In addition, they require a few data to be prepared for the prediction and are able to handle both numerical and categorical data. Furthermore, they are relatively faster than other classification models [22]. In the bathroom monitoring task, since the environment multimodal numeric features (light, temperature, and humidity) are going to be fused with categorical features provided the sound statuses and the decision tree approach are adopted to classify situations which are currently taking place in the bathroom.

A graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ consists of a finite, nonempty set of nodes (or vertices) $\mathbf{V}$ and a set of edges $\mathbf{E}$ as shown in 0 which represents a decision tree. Each interior node is corresponding to one of the input variables. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf. Several algorithms are employed in designing the structure of decision trees. We employ the C4.5 algorithm for designing the best decision tree. The algorithm was proposed by Ross Quinlan. [24]

Given observation vector $\mathbf{x}$ composed of four input variables including light value, humidity value, temperature value, and sound feature. For the sake of taking sound patterns into account while reducing the sensor-level noise, we convert the sound feature into categories before pouring them into the decision tree classifier. From our preliminary experiments, the average duration time of speaking period is about 1.5 seconds, and it continues for about 6 seconds for flushing sound pattern. Therefore, the sound feature will be categorized into three statuses $\{flushing, speaking, quiet\}$ based on sound pattern comparison similar to the way proposed in Section 4.1 .

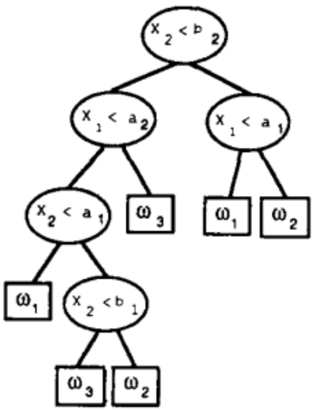


Figure 4-6 Example of a general decision tree. [23]

To perform C4.5 algorithm, we assume that the training sample set is $\mathbf{T} = \{t \mid t \in \Re_4\}$. Each bathroom situation is denoted as a class label $C,\ C \in \{C_{taking\ a\ shower}, C_{flusing}, C_{talking}\}$ where $C_{taking\ a\ shower}, C_{flusing}$, and $C_{talking}$ respectively represent *taking a shower*, *flushing*, and *speaking*. In the first stage, **T** will be partitioned into n subsets $\{\mathbf{T_1, T_2, ..., T_n}\}$ based on the value of a single attribute. Classes of samples in one subset are as much as possible to be the same. Therefore, the decision tree for **T** contains a decision node identifying the testing policies and one branch for each possible outcome. The same procedure is recursively applied to each subset of training samples separated by **T**. The successive divisions to the subsets of training samples proceeds until all the subsets consist of sample belonging to a single class. The goal of C4.5 algorithm is looking for a compact decision tree. Hence, a second stage procedure will choose the most discrimination test policies for each node by calculating the criterion of information gain by utilizing test x to partition training data sets.[24]

Chapter 5 Evaluation

5.1 Experiment Settings

The experiments were conducted in the nursing room 9A03 in National Taiwan University Hospital. Patients in 9A rooms are mostly taken abdomen surgical operation. Heterogeneous sensors are adopted in pervasive sensing room. The floor map and the emplaced sensors are shown in Figure 5-1.

To avoid disturbing elderly patients, we utilize persistent power supply rather than batteries so that we can free from the burden of replacing batteries However, there is limited number of power plug sockets, and the utilization of extension cable is also limited. As a result, how to centralize the power supply spots for all sensors becomes a problem. Three power plugs have been occupied by our system while there are still five more empty plugs that cannot make residents feel inconvenient. Figure 5-2 shows the way to centralize power supply when deploying multimodal sensors into real-world environment without damaging original nursing room.

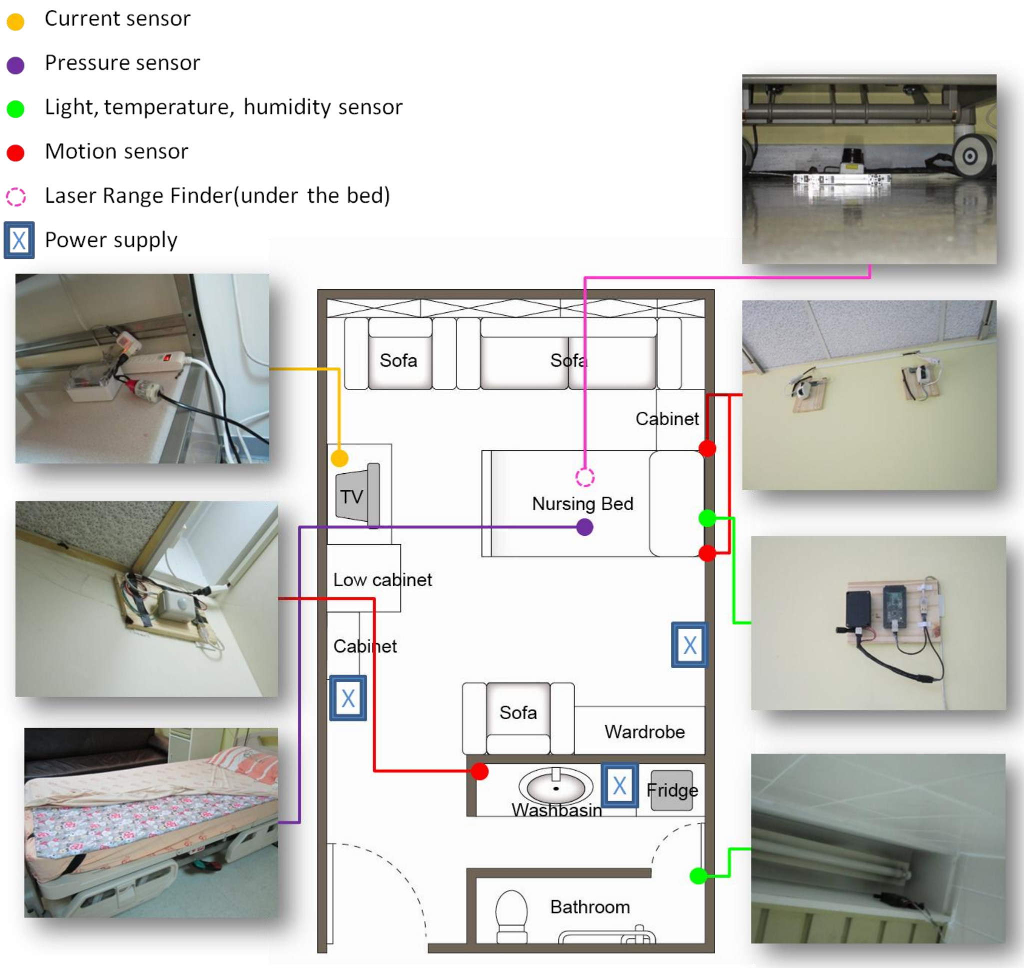


Figure 5-1 Sensor deployment in experiment setting

Figure 5-2 Centralized power supply

(a)

(b) (c)

Figure 5-3 Proposed pervasive healthcare environment (a) the nursing room (b) the entering zone of bathroom (c) bathroom

Figure 5-3 shows the snapshots for both nursing room and bathroom environment after deploying pervasive sensors.

To annotate what situations is occurred, we design a precise monitoring interface as shown in Figure 5-4. The left side of monitoring interface provides the information about each sensor states. All the environment statuses will appear in the upper side. Any triggered sensor will make its corresponding label change color into red. The right side is the labeling interface for the data recorder. Table 5-1 lists all interested activities in

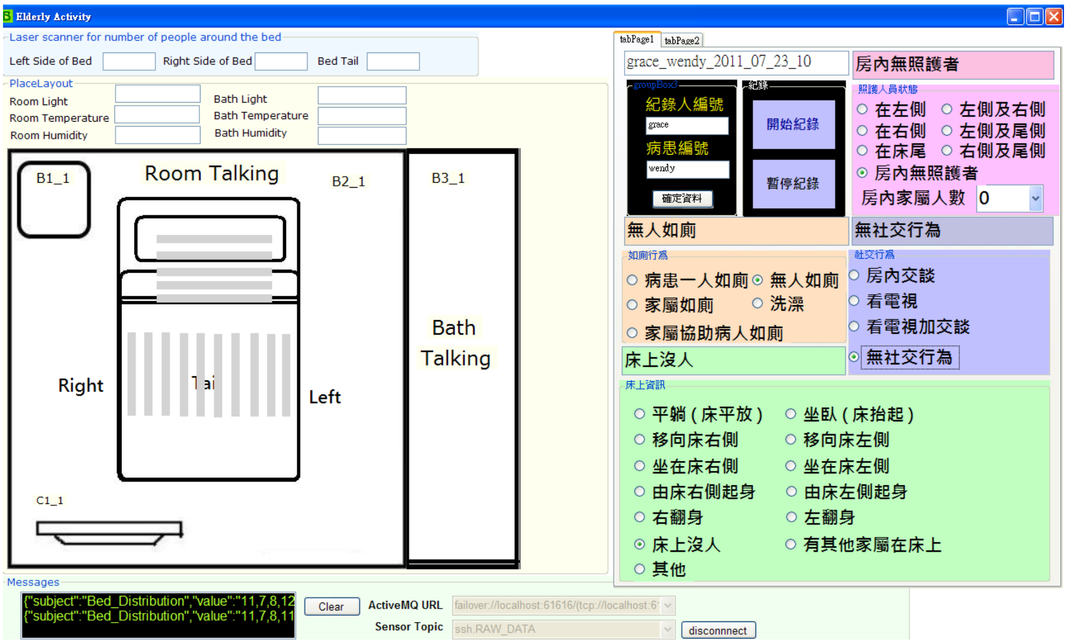


Figure 5-4 Monitoring and annotation interface

this work.

Experiments were conducted by five participants. Due to the limitation time in the hospital, we adopted scenario-based experiments aiming at simulating a realistic life at

Table 5-1 Interested Situation

Social Engagement	**Bed-area Activity**
Watching TV	Leaving Bed
Chatting	Lying on Bed
Watching TV while Chatting	Sitting on Bed
Bathroom Activity	Turning body over to Left/Right
Flushing (the toilet)	**Caregiver Presence**
Taking a shower	Caregiver Presence
speaking	Caregiver Absent

hospital. The scenario will guide participants performing target activities in an arbitrary order.

5.2 Experimental Results

This section presents the experimental results pertaining to several aspects such as social engagement, bed-area events, zone occupancy, and bathroom events.

5.2.1 Social Engagement

To evaluate the total time of social engagement, we monitor the watching TV and chatting events. Table 5-2 shows the recognition result of social engagement. Some short duration speaking events and conversation in low volume will not be detected. However, major parts of speaking events can be successfully detected.

Table 5-2 Recognition rate of social engagement activities

Activity	**Precision**	**Recall**
Watching TV	99.5%	99.6%
Chatting	92%	95.3%

5.2.2 Bed-area Situation Monitoring

In the first steps of bed-area situation monitoring, pressure vector will be clustered by *k*-means classifier. Several tests have been conducted to adjust the suitable *k*. Figure 5-5 shows the result of setting *k* from 7 to 12. By observing the duration of S-R (moving to the right from sitting, referring to Figure 5-5), the state transitions when the k is set to 10 or 11 will be more detail, which means there are four cluster number changes within the S-R situation. The cluster changes are only 3 if the k sets 7 to 10. However, too many clusters will introduce over fitting problem. From Figure 5-6, although the resident is now lying on bed, both 11 ot 12 clusters k-means classifiers cannot correctly detect. After analyzing each situation, *k* is set to 10 for *k*-means classifier.

After classifying each pressure vector into corresponding cluster, a sequence of mapped cluster number will be segmented into episode. Each episode of cluster numbers will be further fed into Hidden Markov Model. Table 5-3 shows the result of bed-area situation recognition. The results show that the proposed approach is promising in detecting various human behaviors.

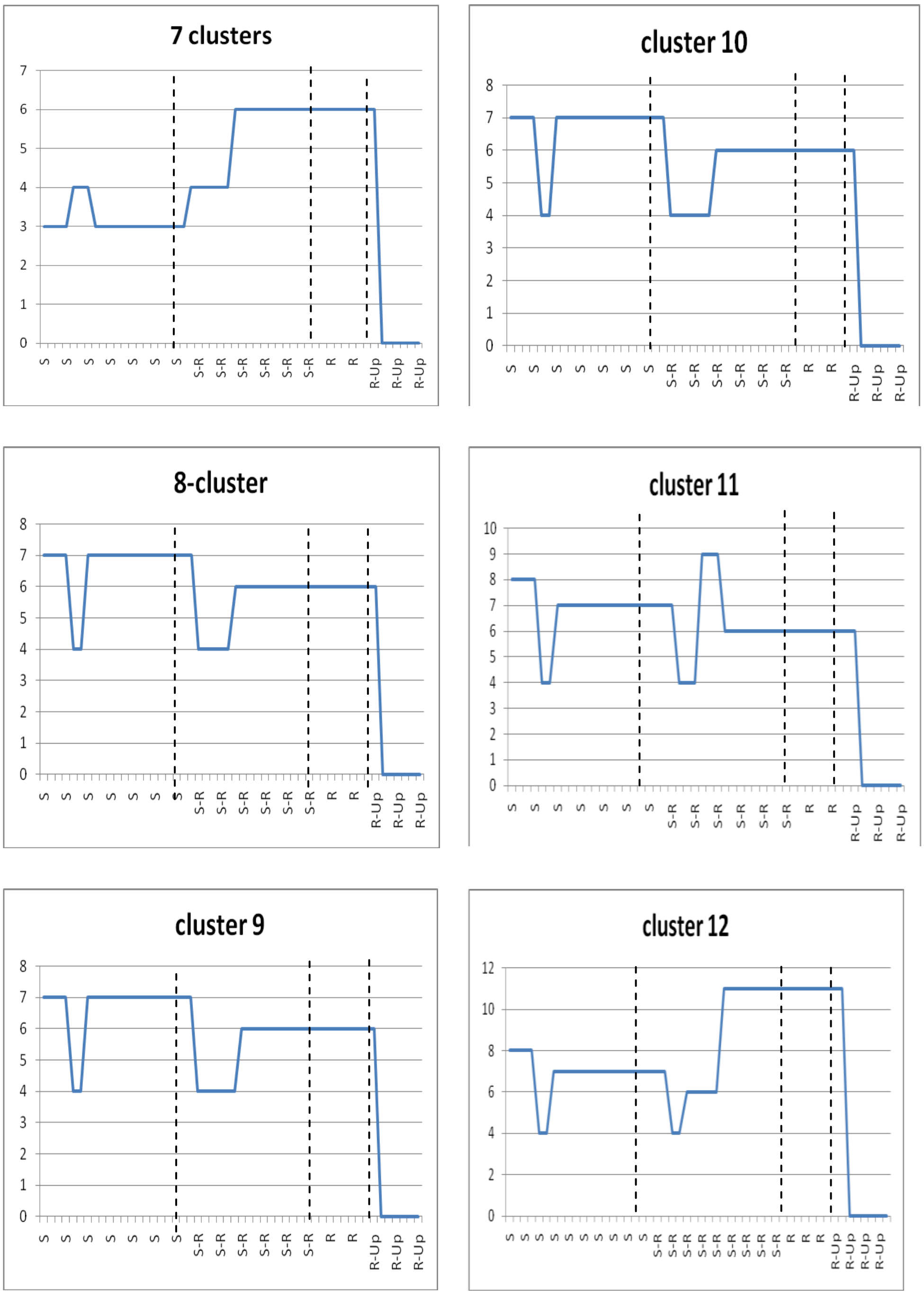


Figure 5-5 Results of *k*-means clustering from sitting to leaving bed from the right side. (S : Sitting state, S-R : Moving to the right from sitting, R: sitting on the right side of the bed, R-Up: standing up from the right side of the bed)

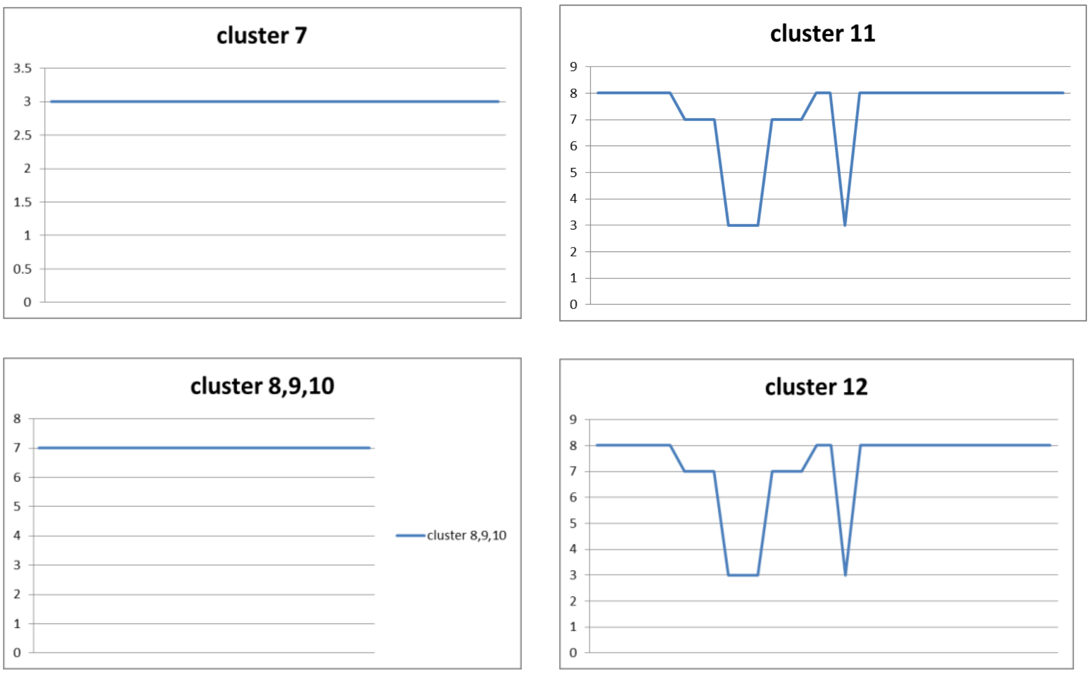


Figure 5-6 Result of clustering for lying on bed

After projecting each pressure vector into corresponding cluster, a sequence of mapped cluster number will be segmented into episode. Each episode of cluster numbers will be further fed into Hidden Markov Model. Table 5-3 shows the result of bed-area situation recognition. The results look promising in detecting various human behaviors.

Table 5-3 Recognition Results of Bed-area Situation Monitoring

	Precision	*Recall*
Lying on Bed	90%	95%
Leaving Bed	98%	97%
Turning over to the Right/Left	93.2%	96.3%
Sitting on Bed	92%	93%

5.2.3 Zone Occupancy Detection

The result of detecting whether a caregiver is in the active zone is present in Table 5-4. In this experiment, we assume that the patient is lying or sitting on the bed. Some caregiver presence events are not detected. The caregiver may put their feet on the sofa while sleeping so that neither laser nor motion sensors can detect the caregivers' presence.

Table 5-4 Recognition rate of caregiver detection

Situation	**Precision**	**Recall**
Caregiver Presence	98.5%	91.6%
Caregiver Absent	92%	99.3%

5.2.4 Bathroom Situation Monitoring

In bathroom situation monitoring, environment status sensor and the sound sensor will be incorporated to monitor on-going situation. Results in Table 5-5 shows the high precision and recall for the taking a shower event. For the flushing situations, it will be affected by taking a shower since in the beginning of the shower, both temperature and humidity are in ordinary which make our system misclassify the taking a shower as flushing.

Table 5-5 Recognition rate of bathroom situation detection

Situation	Precision	Recall
Flushing	80.5%	95%
Taking a shower	98%	92.3%
Speaking	92.5%	95.2%

5.3 Implemented Applications

The purpose of monitoring situations of the elderly people is for the sake of giving assistance for them directly even when their caregiver is not besides. Moreover, automatically generate the health report for the caregiver can help them get the health status of the elderly people in long-term care.

Several applications have been prototyped through iteratively discussing with other field experts; following are the details about the ideas of our applications.

5.3.1 Persuasive and Reminder System for Elderly

Aiming to support appropriate assistance for the elderly people, we design a persuasive and reminder application based on the proposed system to promptly interact with the elderly based on their on-going activities. To make the interface more user friendly, we create a virtual actor called the *Home Keeper Rabbit*. The animations and voices of the *Home Keeper Rabbit* serve as the avatar of a given caregiver. The *Home*

(a) (b) (c)

Figure 5-7 (a) The *Home Keeper Rabbit* is executing counting task when an elder walks using the enhanced walking cane (b) Firework animation used to praise the elderly for reaching a predefined number of walking steps. (c) The animated rabbit sits when the elderly is sleeping

Keeper Rabbit shown in Figure 5-7 is counting the steps of the aged walking using our enhanced walking cane. The number on upper right corner displays the total steps the aged has walked up to current time. When the elderly keeps walking for sufficient steps, the *Home Keeper Rabbit* will praise to his/her work (shown in Figure 5-7 (b)) and cheer on the elderly to exercise as much as possible.

Table 5-6 shows the currently implemented functions of our *Home Keeper Rabbit*. Whenever an activity of interested in the table is detected, the system will automatically provide its corresponding feedback.

Table 5-6 Timely reminders or encouragement for target activities.

Detected Activities	Description of system feedback
Sleeping	If a sleeping behavior is detected, the system automatically plays music for a while.
Sitting on bed	When the elderly wakes up and sits on the bed from sleeping, the *Home Keeper Rabbit* performs an animation with a cheerful greeting.
Using Walking Cane	Current number of steps will be shown at upper right corner of the screen.
Leaving bed	When the user is about to leaving the bed, the *Home Keeper Rabbit* reminds its potential hazards (i.e. tripping) and inspires the elderly to do more exercise.

Table 5-7 Persuasion policies supported for interested activity episode.

Activity episode	Description of system feedback
Sleeping	When an elderly sleeps more than one hour in the *daytime*, the *Home Keeper Rabbit* speaks loudly to wake him/her up
Walking	Four levels of walking states are evaluated. Higher level means more steps the elderly has walked via the walking cane. *Home Keeper Rabbit* encourages the elderly when the elderly reaches a higher level

In addition to timely interacting with the elderly in the event of detecting a specific activity, some other meaningful activity episodes should be considered. We consulted experts in eldercare and they mentioned that the length of daytime sleeping would closely influence the sleeping quality at nighttime. Furthermore, sufficient exercise does help the elderly live healthier. Based on the suggestions, we consider two additional meaningful activity episodes: *walking duration* and *sleeping duration*. Table 5-7 represents the persuasive policies we design for the interested activity episodes. Note that the degree of preference about each service for the elderly is acquired by several interviews, which will be discussed in the next section.

5.3.2 Health Report for Caregiver:

As for realizing an evidence-based report system, we worked closely with medical researchers as well as home caregivers (hereafter referred to as medical consultants) with the aim of navigating the real needs of caregivers. One problem we ask the medical consultants is the trustworthiness of some commonly used medical scales (such as Barthel Index [8]) which are often evaluated based on some pre-designed oral questionnaires. The medical consultants pointed out the difficulty for elderly people to recall precisely about their daily activities when they meet doctors or caregivers. Moreover, some elderly people may exaggerate their condition in order to get more social resources or attention. In order to provide more objective and reliable observations for caregivers, our system can translate all collected evidence of the elderly into easily comprehensive health reports with the statistics regarding their ADLs. By choosing a start and an end date, caregivers can also get a health report in a specified period. We also developed a web-based personalized healthcare portal (or *Help Center*) application for the caregivers to easily get the health reports. In the report, the following health status items are available:

(1) *Activity statistics in a day*: The starting time and interval for each activity episode performed in one day is presented in the form of a Bart chart. The Pie chart will further reveal the ratio of each activity in all day long (as shown in Figure 8).

(2) *Sleeping and walking pattern analysis in a week*: Variations of time interval regarding walking and sleeping activities in the last week are expressed in a histogram. For the *Sleeping* activity, daytime and nighttime sleeping interval will be separately shown in two histograms.

(3) *Leaving frequency*: Leaving frequency as well as is time instances in the past one week are rendered as a point map.

(4) *Total social time*: The total time of the elderly people when they engage social-related activities.

In addition, by choosing a start and an end date, caregivers can get a health report in the specified period.

5.4 User Feedback

There are three sections in our video which include *Sitting on Bed* event, *Leaving Bed* event, and the *Using Walking Cane* event as well as walking episode. Each section shows how the user interacts with the system.

There are three interviewers in our field study. One is the first author of this work who is in charge of answering the technical questions during each interview. The other two are students from the department of nursing. Both of the two nursing students have the experiences in taking care of the elderly. One of the two students has cooperated with our team, so she also understands our work.

For the interviewees, we totally interviewed nine older people, three men and seven women. Each senior underwent a quarter-to-one hour interview process. Two of them were interviewed directly in their own houses; the other seven were interviewed when they were waiting in the hallway of National Taiwan University Hospital. All elderly participants are more than 65 years old. Three of interviewees are the volunteers of the hospital. Four of them live alone independently in the city.

Our system is now in a preliminary stage where the setting of our evaluation focuses primarily on a bedroom-scale environment. To inquire the experience of elders' bed-related habits and to inspire them to think more about their real-life needs, we started the interviews with some sleep related questions: "*Do you have the habit of taking a nap?*", "I*n daytime, approximately how long will you spend on the bed*?", and "*what do you usually do on the bed in daytime?*"

Next, we played the section regarding the *Sitting on Bed* service supported by our system, and we asked, "*Imagine that you wake up and nobody besides you, will you feel attentive when the rabbit saying cheerful greetings to you though it is a virtual figure?*" Among all of our interviewees, five elderly people like our virtual caregiver. "*It will be a wonderful idea if the rabbit can say something when I wake up, but it will even preferable if the rabbit can gives different greetings.*" *(Female, 68s, hospital volunteer, living independently*) Suggestions about providing additional information such as date and weather are mentioned by the interviewees. These will be altogether considered in our second stage system implementation. A statistic is that most of those elderly who live independently lik to hear greetings when they wake up. The other four interviewees didn't like our *Home Keeper Rabbit* mainly cause by their low interest in computer technologies. They rather chose a real human assistance who can pat their backs or turn lights on for them. "*I'd rather like the system accomplish what I really want when I get* *up, not just say hello.*" *(Female, 65s, house keeper)*

Regarding the *Sleeping* service which is an automatic music playing service, six of the interviewees are looking forward to this service since all of them can listen to the music while they are sleeping. Three of the interviewees disliked the service owning to some personal concerns such as their health states or economic conditions. Another participant likes being at liberty to turn on/off the music service by his/herself rather than being automatically provided the service without any notification.

As for the *Leaving Bed* reminder service, although all our interviewees are in good mobility, seven of them gave positive feedback and looked forward to the service in their future lives. They pointed out the importance of such a reminder before leaving bed especially for those who suffer from dementia or Parkinson's disease.

Lastly, we inquired opinions about our *Walking* service, which is a counting task according to the number of steps up to now; six interviewees were fond of this service. In addition, they indicate the need of a virtual sport coach, *"I hope the system can stop me doin*g an excess of *exercise; besides, I need encouragement to do more exercise via appropriate suggestions." (Female, 73s, Hospital volunteer)*

We obtain an unanticipated lesson from our preliminary questions that almost every elderly people we interviewed do not like to sleep on bed in the daytime and they go to bed early at night and wake up early in the morning. Based on this observation, we will alter the design of the original *Sleeping* service which calculates the total span of sleeping and then wakes up the elderly if the span exceeds a pre-defined threshold. By asking some in-depth questions, we also learned that the core idea in an assistive technology for the elderly should be more human-centric. Many interviewees suggested that our system should be able to improve their social connections. "*I hope the system* *can automatically help me contact my children when I get up.*" *(Female, 68s, living independently*) and "*I'd like to contact my friends and discuss whether we c*an hang out today." In addition, the deployment cost and whether the system is easy to use are highly concerned by the elderly people. *"It sounds complicated. I am not familiar with the computer."(Female, 68s, volunteer)* and *"This service sounds too expensive for me. I am not rich enough to own such a smart system" (Male, 80s, living dependently).* However, most of our participant showed optimistic expectation on the system and were willing to visiting our lab.

Chapter 6
Conclusion

6.1 Summary of Contributions

In this thesis, we propose a context-aware and human-centric pervasive healthcare system, which is one of the few works that is deployed in a real-world hospital environment. To deal with problems occurred during the deployment, several novel sensor installation procedures are designed and reported. In addition, we also devise a multi-modal agent architecture for inferring situations of users. The detailed explanations of main contributions can be summarized as follows.

- **Understanding difficulties in existing healthcare environment.**

Rather than paying attention on pure technology design, we do field study to find out the true needs for the healthcare workers. The nursing task lifecycle are summarized to help us analyze difficulties of working in hospital. Observational result motivates us to list potential assistance which can be taken into account by computer science researchers.

- **Utilizing novel non-obtrusive sensor technology in diversity situation monitoring.**

Taking human feeling into account, we preclude intrusive sensors for physical and mental considerations. Novel approaches to incorporated multimodal pervasive sensor in detecting caregiver occupancy, bathroom situation, and social engagement are designed. These alternative approaches give promising results that encourage us to do more experiments in the future.

- **Extensible sensing and monitoring platform**

The agents taking charges in different tasks are independent from each other by loosely coupled system design. Features extracted from sensor reading by centralized process are shared in a public common data communication infrastructure, called the Message Queue (MQ) that can be subscribed by any monitoring agents. Modification, addition, or removing particular monitoring agents will not affect any other agents that in works. This characteristic makes our system has the ability to cooperate with other applications that can be communicated with MQ.

- **Moving out from the laboratory**

The finally contribution is that this work collaborates with domain experts from multiple domains. In addition, the system is deployed in a real hospital environment. How to make it possible to be accepted by medical staffs and elderly patients are non-trivial tasks and we gain many precious experiences from these collaborations.

6.2 Future Work

Many research works can be done to extend this work. The most important ones are listed below:.

- **Develop more monitoring agents to assist nurses in their ordinary tasks**

Based on the observational result in Chapter 2, we have realized several difficulties for hospital workers. Some of them have to be explored further. For example, how to monitor the exhausted status of intravenous drip is the most expected application for nurses. Monitoring the taking medicine time and having meals are also good trials to help medical staffs estimate the recovery of elderly patients.

- **Gather more suggestions from medical staffs and elderly patients**

Although we have brought the system into a real hospital, target users are not enough to give us sufficient suggestions. We have to try much harder to encourage elderly to get used to pervasive healthcare technologies in the future.

- **Cooperate with other applications in healthcare researches**

The proposed healthcare system is extensible. Any other research groups that can put their application into MQ can be incorporated in the environment. For example, the data from activity tracker Fitbit can be involved into our system since it can communicate with MQ. We expect the aggregation of healthcare research groups in the future.

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