An Empirical Study on Engineering a Real-World Smart Ward Using Pervasive Technologies

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***Abstract*—The shortage of medical staffs has become a critical issue due to the rapid growth of aging population. Numerous attempts have been made on devising pervasive healthcare systems to precisely and continuously monitor patients' health status. However, the transformation from prototypes in the laboratory to practical systems in a medical institution is still a challenging task. This paper reports our progress and lessons learned from designing and deploying a pervasive healthcare system that runs persistently for more than six months in a real-world smart ward of National Taiwan University Hospital, one of the most heavy-loaded hospitals with high occupancy rate in Taiwan. We describe techniques proposed to deal with three essential challenges: design for essential needs, design for user acceptance, and design for maintenance. The system is evaluated empirically by deploying two applications in the field. Based on the results of field interview and questionnaires, we believe that this work is a milestone of a persistently running pervasive healthcare system deployed in a hospital.**

***Index Terms*—Context-aware services, context awareness, health information management, pervasive computing, sensor systems and applications, systems design.**

I. Introduction

In a medical institution, the activity of daily living (ADL) is a well recognized important indicator of a patient's condition. Usually, ADLs of a patient are reported either by periodical interview or self-report, which can be subjective, less responsive, and error prone. Unfortunately, these subjective self-reports are still the main sources for medical treatment decisions in most institutions. Over the past few years, a considerable number of studies have been conducted on applying the pervasive technologies [1] to enhance healthcare and wellness management. By combining well-developed technologies such as sensor networks and machine learning algorithms, one can design a pervasive healthcare system that detects and analyzes patients' ADL autonomously and thus reduces the burden of medical staffs and caregivers. From the perspective of pervasive technology, ADL is usually referred as "situation" information, where "situation" is the perception of an entity in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future [2]. In simple terms, situations are high-level contexts (yet still a type of context) that can be obtained by a thorough understanding of state interactions and implication from several basic contexts information.

It is commonly agreed that medical institutions are substantially different from normal environments such as domestic places, schools, or museums. Therefore, detecting patients' situations in medical environments brings about new challenges for designers of pervasive healthcare systems. Such systems are "ordinary and extraordinary human computer interaction" [3]. Taking smart wards as an example, it is where ordinary people (able-bodied medical staffs) and extraordinary people (patients) operate in extraordinary environments (wards with patients; heavy loaded and stressful). Although considerable works have been dedicated to developing pervasive healthcare systems, most of them are still prototypes in the laboratory. Thus, we could only focus on technological aspects rather than the practicability of systems. As pointed out by Bricon-Souf and Newman [4], the transformation from a prototype pervasive healthcare system to a practical one is still a challenging task. It follows that designing a practical pervasive healthcare system to identify patients' situations is not quite as simple as deploying a bundle of sensors, applying data processing algorithms, and then presenting the results. More efforts are required to find out the real requirements and real design issues of the system that detects situations of "extraordinary people (patients)" and operates in an extraordinary environment (hospital) in the field.

Based on the above viewpoints, we focus on bridging the gap between existing pervasive technologies and the real-world challenges. Our approach begins by conducting a comprehensive field observation and then understanding the requirements through these studies. Then, the overall system design concept is guided by the insights obtained by conducting interviews with several domain experts working in the real-world medical environments. The system development process also involves considerable multidisciplinary teamwork with medical staffs and psychologists.

Reflecting on our experiences, the main obstacle in building a pervasive healthcare system in the field is threefold.

1) *Requirement*: Constructing hardware and software for detecting patients' situations takes a considerable amount of time and money. Without a comprehensive field study, a system designer is unable to identify the essential part of patient situations that the medical workers are eager to know and monitor.

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2) *Acceptance*: Patients live in the hospital often before or after surgery and are relatively frail. To prevent medical dispute, medical staffs and caregivers are typically conservative against the deployment of new technologies. The privacy issue and safety considerations are mostly concerned when deploying pervasive technologies. Using rich sensors such as camera or microphone is usually impossible.
3) *Maintenance*: Most hospitals are typically of high occupancy rate. There is little time for resetting a used ward. System maintenance and sterilization of the ward must be performed in parallel within few minutes. Also, in emergent situations, the occupied sensors (such as a smart mattress) should be able to be undeployed safely by medical workers in a short time.

The purpose of this work is therefore to report our experiences of dealing with the challenges mentioned above. Core contributions of this research are summarized as follows.

1) *Design for essential needs*: It is crucial to consider the real needs of the user of the system. This work conducted a comprehensive field study around the target environment and identified four essential situations of patients that are most helpful for medical workers, as detailed in Section II.
2) *Design for user acceptance*: In a real-world environment, the sensors must be carefully designed so that they bring least security and privacy concerns. This paper illustrates the design and implementation of sensor furnishing used to gather essential situations. The details are reported in Section III-B.
3) *Design for maintenance*: This paper proposes a practical architecture to promote ease of maintenance and to obtain more informative results from simple contexts. Sections III-A and III-B describe the detailed design.

In summary, this paper presents the lessons learned from designing, deploying, and maintaining a persistently running pervasive healthcare system in a real-world smart ward of National Taiwan University Hospital (NTUH), one of the most heavy-loaded hospitals with high occupancy rate in Taiwan. We hope that future research in this field can benefit from the practical experiences presented in this work.

II. Field Survey

This section presents results of conducting structured observation to address the *design for essential needs* research objective. We adopted an ethnography-like approach to probe requirements. Ethnography is the systematic study of people and cultures. Recently, it also became a popular qualitative method for information systems design as it leads to robust understandings of dynamics in human activities [5].

The field survey was carried out around the wards on the 9th floor, section 9C of NTUH. Patients in section 9C are mostly before or after treatments of digestive diseases. We conducted the field survey based on the following procedure.

1) We performed a comprehensive field survey in the field. In total, ten full working shifts around the wards in section 9C of NTUH were observed and recorded.
2) We examined the results and listed all possible situations that could be helpful to the medical workers.
3) We carried out a semistructured interview individually with nurses in section 9C and then confirmed the situations derived in step 2 with them. After the session, several situations of interest were listed, where some of them were proposed by the nurses.
4) We proceeded to a focus group session to discuss the importance of these situations. The session is helpful for complementing and clarifying structured observation. As a result, the top-ranked situations to be detected were selected.

Details are reported in the following sections.

A. Nursing Process

We recorded observations in the working shifts. After finishing a nurse working shift cycle, we discussed with the nurses and probed the difficulties they faced in the shift. Next, we proposed a list of potential assistances for the medic staffs and asked for their advice. We define one complete shift begins in shift changing from previous working shift and ends after changing to the next shift. The occurred activities, used artifacts, and participants involved are recorded. The first task within a nurse shift is to deliver the information of patient conditions from the current duty nurse to the next one. This process elapses 30 min in average. Information passed between successive nurse shifts includes the contents or quantities of intravenous drip, medicines the patients have taken, and the appropriate food type of the patients. We observed that although the recovery progress of a patient is important, such information is seldom passed between successive nurses. The reason being it is hard to assess recovery status objectively. After exchanging patient information, the duty nurse prepares necessary medical materials in the nursing center. The medical material preparation process takes about 20 min. After that, the nurse starts to run the ward round and visits patients. In NTUH, each nurse is responsible for 13 patients in average per working shift. Typically, a patient visiting process can be generalized into three stages: precaring, oncaring, and postcaring. Activities of nurses in each stage are described as follows:

1) *Precaring*: Before entering an appointed ward, the nurse pushes the nursing cart toward the target ward and places the cart outside the door. The nurse first reviews the handover data of the patients provided by the previous duty nurse and then pushes the cart into the ward. Afterward, the visiting nurse confirms the name and age of each patient. For those who cannot describe themselves clearly, the nurse checks their bracelet containing personal information. Next, the nurse greets the patient and then starts performing the nursing task. Besides the recovery progress of the patient, the nurse often cares about the social relationship among the patients and caregivers. For instance, the nurse usually asks the caregivers about recent occurrences. This helps to increase social relationship among nurses, caregivers, and patients. In our interview, the nurses reported that the better the social relationship among nurses and caregivers, the more they trust the medical staff. Thus, the atmosphere in a ward

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becomes positive. We also observed that patients are more joyful if the caregivers chat with them frequently.

2) *Oncaring and postcaring*: In these phases, nurses check the environment status of the wards such as temperature and humidity. We found that nurses have to adjust the air conditioner very often when visiting the patients. This observation reveals that caregivers are usually unconscious of inappropriate environmental status. After that, the nurses start to do the main nursing task such as drip-injection/drip-extraction process, blood pressure measurement, and giving prescribed medicine. We found that although a nurse has taught the caregiver about how to stop the drips, however, upon seeing the drips about to be exhausted, the caregivers are always so nervous that they press the emergency call or directly come up to interrupt the nurses even when she/he is working on another patient. When measuring blood pressure, the nurse has to record the measurement manually on the laptop. Then, the nurse reports the measurements and informs whether the patient is in good condition. In fact, it can be tedious for a nurse to type the measurements as she/he has to move back and forth between the bedside and the nursing cart. To supply prescribed medicine, the nurse gives a little cup containing all the medicine pill that patient has to take. The nurse usually reminds patients the correct taking time by recording the time on the cup. Patients usually forget to take the medicine at the right time. Finally, the nurse evaluates the recovery status of the patient and then informs the estimated time of discharge from the hospital.

B. Findings

According to the results, most medical workers expect to know how many times the patient leaves from the bed and try to walk around. They also mentioned that if a patient does not leave the bed soon after surgery, the wound caused by the surgery very likely ulcerates. Besides food, water, and medicine intake status, toileting time monitoring is also important. Moreover, the nurses also care about whether the caregivers are accompanying the patients. Caregivers can help to monitor patients' status when nurses leave the ward. Finally, the activity level is also helpful when evaluating recovery progress of a patient. Finally, we listed indicators that appear to be important for understanding the recovery status of patients. Then, we conducted a focus group session consisting of eight medical workers in the nursing station and then selected the top-ranked situations. The selected situations are bed situations, bathroom situations, social engagement, and presence of caregivers. Among these situations, bed situation monitoring is most mentioned.

III. Design

Based on the lessons learned from on-site observations and interviews presented in Section II, we identified several essential system objectives that are most helpful for medical workers in a smart ward.

1) *Bed situations:* Bed situations are difficult to be observed by human labors. For example, it is important to turn a patient's body over periodically to prevent bedsore. Without a pervasive healthcare system, the only approach is to record the turning time manually. It turns out to be a burden for both caring nurse and caregivers. Leave-bed detection is also helpful, since medical workers expect to know the leaving bed event under abnormal conditions such as low illumination or when there are no caregivers around the ward. Also, bed-side situations can be used to estimate the progress of recovery.
2) *Bathroom situations*: The toileting frequency information can indicate the digestion recovery status. Automatically recording toileting frequency is important as it is hard for a patient to remember and to report manually. In addition, the system is expected to alert nurses when an emergent situation occurs in the bathroom.
3) *Social situations*: Social engagement is a critical indicator to estimate mental, instead of physical, health status. Although other approaches such as interviews or field observations can be used, we believe that a pervasive healthcare system with ambient sensors will be the best way to monitor social engagement as social interaction can occur anytime.
4) *Presence of caregivers*: Medical workers expect to be promptly informed whenever the caregivers are not in the ward. It can be dangerous when the patient is left alone in the ward. It motivated us to design a system which can automatically detect whether the patient is alone.

The following sections describe the overall system architecture and the design of hardware and software components in detail.

A. Architecture

As mentioned, to *design for maintenance*, the system architecture has to be designed so that the components are loosely coupled, reliable, and flexible. In our system, all components interact based on message-oriented middleware (MOM), which is an event-based mechanism that enables asynchronous communication and loosely coupled integration. As what have been shown in our previous work [6], the MOM-based pervasive system is typically more flexible and reliable than other architecture styles. Fig. 1 provides a vertical structure of the system. The data flow from the bottom to the top, and then are persisted to a situation database. The persisted results can be categorized into two types: situation records and situation interval records. The former describes an environmental state at a specific time whereas the latter refers to a set of continuous events. The situation interval records are derived from the situation records by interval segmentation. The detailed functionalities of each layer are explained as follows.

1) *Data retrieval*: A sensor network is deployed in the ward. A possible output of this layer looks like $[P_3, 0]$, which indicates a 0 read value for pressure sensor P_3 deployed on the mattress. In order to not to interfere with patients' daily activities, the wearable sensors and privacy-intrusive sensors such as cameras should be avoided.
2) *Context extraction*: This layer consists of a set of components that translate the raw data into contexts. The translation logic is usually application specific. For example,

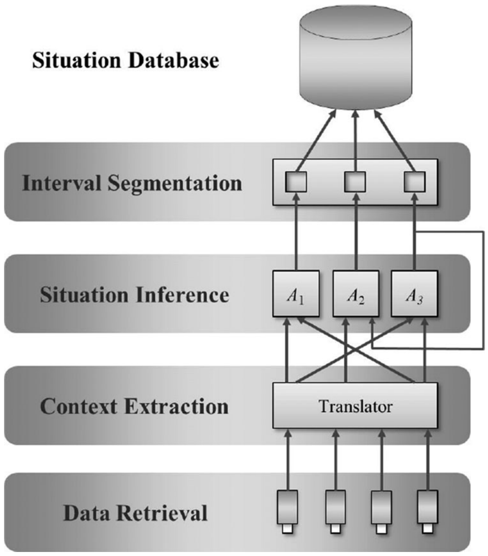


Fig. 1. Vertical structure of the system.

one can determine a threshold and accumulate the values above the threshold. A possible output of this layer can be [*"upperbed," "off"*], which indicates that the pressure sensor deployed on the upper bed is not pressed.

3) *Situation inference*: Components belonging to this layer perform situation inference (usually by using machine learning techniques) from contexts. Specifically, this layer consists of several independently running inference components, each of them subscribes a set of context or situation topics in MOM and is responsible for identifying a specific situation based on these data. For example, the situation [*"lyingpose," "leavebed"*] can be inferred after inspecting all pressure-related contexts. Note that some situations can be obtained by cascaded inferences. For example, if a situation [*"caregiverpresent," "false"*] is perceived, then [*"lyingpose," "leavebedalone"*] may also inferred. Also note that since our system is designed based on MOM, one can easily extend the situation recognition capability of the system by introducing new inference components.
4) *Interval segmentation*: Sometimes it is more informative to show the exact period of a given situation to the caregivers. Hence, this layer exists for aggregating consecutive contexts or situations into one interval record. For example, [*"lyingpose," "01/10 12:03:54," "01/10 12:15:39"*] is a situation interval record. As part of the output, the situation records, generated in the situation inference layer, can be retrieved from the MOM. Meanwhile, the situation interval records can also be retrieved after persisting to the database.

B. Sensor Furnishing

To gather information in the wards, we design and implement a set of sensing furnishing consisting of wireless sensors such as pressure sensors, current sensors, motion sensors, light sensors, sound sensors, and humidity sensors in the room. The data gathered by these sensors are useful for analyzing human behaviors or interactions between people and daily objects. We also use a laser range finder (LRF) under the bed to detect the location of people. Special consideration related to the *design for user acceptance and maintenance* research objective is taken into account.

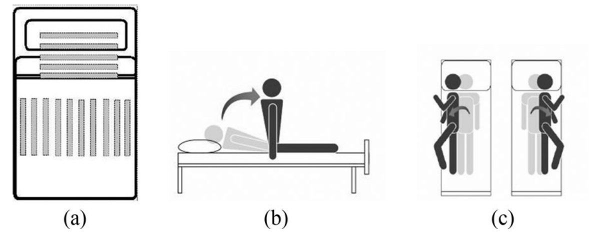


Fig. 2. Design of pressure mattress for the nursing bed. (a) Layout of sensors in the pressure mattress, (b) lengthwise body movement, and (c) lateral body movement.

1) Sensor Mattress for Bed Situations Monitoring: The interested bed situations include leave-bed detection and body movements on the bed. Many mattress prototypes or products are available, but these works neither provide sufficient detail of sensed data for further analysis nor are suitable for medical use in the ward. For instance, Arcelus *et al.* [7] used a region of interest detection algorithm to extract regional signals. Their work is optimized for leaving bed detection so that it was difficult to use their work to detect other situations. Hsia *et al.'s* work [8] can detect postures on bed using principal component analysis. However, their approach does not consider the temporal transformation of on-bed situations so that it can only monitor postures at a particular time. Beddit [9] is a commercial off-the-shelf product that is primarily used to estimate sleep quality. The limitation of Beddit is the insufficient details of sensor data. Taking Beddit classic as an example, it only provides interpreted situations such as sleeping time, time to fall asleep, sleeping efficiency, and heart rate.

Consequently, to obtain detailed signals and facilitate sophisticated analysis, we made a pressure mattress consisting of pressure sensors that can measure the distribution of pressure values. The activities or postures of the patient can be inferred based on the distribution of pressure values. The mat is placed between the bed and the bed sheet so that the sensor mat is portable and medical workers can easily deploy and remove the pressure mat without technical knowledge. The portable pressure mat consists of two layers. The upper layer is a cushion that makes it comfortable to lie on the mat; the lower layer comprises an array of pressure sensors. If medical workers want to clean the bed sheet, they can easily take away the sheet and put it back after cleaning.

Besides, dealing with the deformable nursing bed is also challenging. Deformation leads to incorrect measurements and damages the sensors. To deal with this problem, we arranged the sensors in different directions so that the sensors on the mattress can avoid the folding lines caused by deformation, as shown in Fig. 2(b) and (c). Similarly, we arranged the sensors horizontally to monitor lengthwise body movements. The sensors are arranged horizontally [see Fig. 2(a)] so that the system can

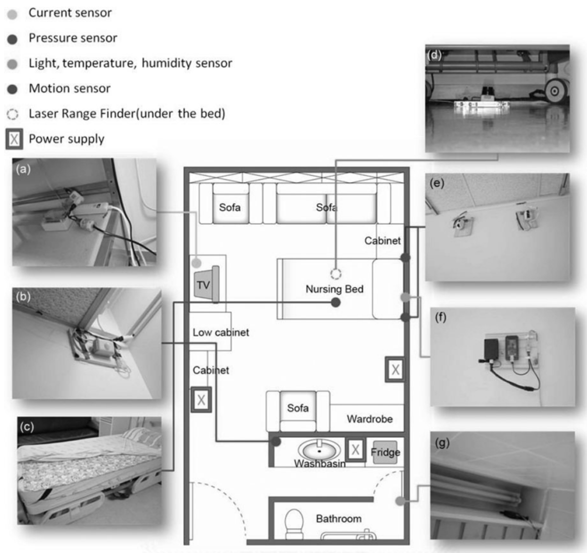


Fig. 3. Floor plan of the smart ward.

detect whether the patient is lying on the bed. For the lateral body, sensors are deployed in the lower region vertically so that the system can distinguish the gravity shift from center to the left or the right side of the bed.

2) Bathroom Situations Monitoring: The main interested situations in the bathroom are emergency detection (a patient falls), toileting, and taking a shower. The system is expected to acquire these situations without violating privacy concerns. Hence, it is apparent that rich sensors such as microphones and cameras cannot be used. Also, the nurses point out that it is not appropriate to use wearable sensors, as it can be harmful or disturbing to the patients. As a result, the main challenge is how to detect situations accurately with a set of simple sensors. The light, humidity, and temperature sensors are useful to detect situations in the bathroom. For example, the humidity and temperature readings are much higher than usual if a person is taking a shower in the bathroom. A simple low-resolution sound sensor that is only able to detect sound intensity is also used to detect toilet flushing and human speaking [see Fig. 3(g)]. To ensure human presence, we also deployed a motion sensor on top of the entering zone [see Fig. 3(b) and (g)]. In this way, the system can identify an abnormal situation such as a person entering the bathroom but not going out for a period of time.

3) Sensors for Social Engagement Monitoring: Social engagement situations are helpful for probing the mental health conditions of a patient. This kind of situations can be categorized into two types: interactions among people with mediating objects and interactions without mediating objects. For example, if a caregiver and a patient watch television together in the ward, the television is the mediating object that facilitates the interaction between one another. Social engagement mediated by objects can be detected by monitoring the power usage of appliances. Hence, we mounted current sensors to the television to monitor the total watching time. We also employed sound intensity sensors to detect the interactions without mediating objects. The deployment of social engagement sensors is shown in Fig. 3(a) and (g).

4) Sensors for Zone Occupancy Detection: The major purpose of zone occupancy detection is to infer the number of people (excluding the patient) in the ward. It is hard to determine zone occupancy using only a motion sensor, as most of the time, there is at least one person in the ward (i.e., the patient), and movements of the patient can trigger the motion sensor. Also, camera and wearable devices are not preferable due to privacy and safety concerns. Our approach was to deploy a mini LRF under the bed, which can scan the ward and report the number of people accurately in real time by calculating human legs. In this approach, the measurements obtained from the LRF are decomposed into several sectors. Then, a probabilistic model is used to compare these sectors with leg patterns to check if any of them belongs to the set of human leg patterns. Next, it examines the promising leg sectors with a modified inscribe angle variance method to confirm if the sectors conform to human leg's arc features. Details of the detection mechanism are described in [10].

C. Situation Inference Algorithms

As mentioned in Section III-A, the retrieved raw data is preprocessed by a context extraction component so that it is easier to perform situation inference. For example, to estimate bed situations, all sensor readings coming from the mattress are fused to represent the pressure distribution of the pressed area. After that, the extracted contexts are sent to MOM and transmitted to the corresponding bed situation inference component. Every situation inference component is equipped with different classifiers or algorithms and works independently. The design of each situation inference component is detailed below.

1) Bed Situations: The bed situations inference components receive a vector of pressure values from MOM. The interested bed situations include lying on the bed, sitting on the bed, leaving bed from the left/right side, and turning the body over to the left/right. One interesting point to observe is, the key to identifying the bed situations is that these situations are highly dependent on temporal relationships. Thus, we denote temporal relationships between each observed context using hidden Markov model (HMM).

To improve the reliability of results, we use *K*-means cluster to group the data first. The received vectors are first projected into clusters, where a cluster is used to group similar samples. Given a training sample set $\mathbf{T} = \{\mathbf{t}_i | \mathbf{t}_i \in \Re, i = 1, ..., N\}$, where each t_t is a processed vector coming from a *K*-means classifier, we incrementally test different number of clusters and choose the best number for T. Then, we use a *K*-means clustering method to partition all training data into k sets that minimizes the within-cluster sum of squares (WCSS),

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

where $\mathbf{S} = \{S_1, S_2, ..., S_k\}$. To build a *K*-means classifier, the assignment step and the update step are executed alternatively. In the assignment step, for each training sample t_j at time t, the Euclidean distances between the sample point and each clustering centers at time t are calculated. The sample point is clustered as set i if the distance from center is the shortest among all the other centers, namely,

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

In the update step, the new means of cluster i is refined after a new sample point is added to it,

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

where $\mathbf{t}_j \in \Re$.

The transition from one bed context (an on-bed posture with a timestamp) to the next is called a Markov process, since the upcoming state depends only on the current state and the fixed probabilities based on observing the past behaviors. For each interested bed-area situation, we establish one independent HMM. As a result, six HMMs are incorporated to classify received observation sequence: $\lambda_s = (M_s, A_s, \pi_s), s = 0, 1, ...6$. Given a sequence of observations, the inferred situation at time t is determined by considering the highest likelihood of observation sequence O,

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

where the likelihood is obtained by the following equation:

$$P(O|\lambda_s) = \sum_X P(O, X|\lambda_s) = \sum_X P(O|X, \lambda_s) P(X|\lambda_s).$$

2) Bathroom Situations: In a bathroom, weak sensors are more feasible in detecting bathroom situations because of privacy concerns. To increase the precision, the system examines a sequence of observations and then matches the observations to a decision flow. For example, we deployed a motion sensor in the gate zone [see Fig. 3(g)]. If a person is going to the bathroom, then the motion sensor will be triggered. Entering the gate zone does not imply that a person is going to "use" the bathroom. Instead, if a person enters the gate zone and the bathroom light is turned on, then that person is going to use the bathroom. More concretely, whenever a motion sensor is triggered (ON), event A is emitted and a time window of T seconds is then initiated. Before the window expires, if the light sensor detects that the light state changes from a low lumen to a high lumen, event B is emitted.

The decision process described above makes it suitable for using decision tree learning approaches, which creates tree-like models and uses them to predict the value of a target variable based on input observations. Here, we employed the C4.5 algorithm [11] for designing the best decision tree. To perform C4.5 algorithm, we assume that the training sample set is $\mathbf{T} = \{t | t \in \Re\}$, and each situation to be recognized is denoted as a class label C, where $C \in \{C_1, \ldots, C_j\}$. In the first stage, T is partitioned into n subsets $\{T_1, T_2, \ldots, T_n\}$. 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 proceed until all samples of these subsets belong to a single class. The goal of the C4.5 algorithm is to look for a small decision tree. Hence, during the second stage, we first calculate the score of each discrimination test policy based on information gained by applying the policy to partition training datasets. Then, the discrimination test policies with test score are chosen for each node.

3) Social Engagement: The social engagement recognizer can recognize two situations: watching TV and chatting. Here, the system performs statistical analysis on temporal sound intensity to determine whether people are chatting in the ward. The sequences of sound intensity patterns are also aggregated to assist in determining whether a conversation is still under way. We conducted several in-house experiments to collect the patterns of human conversation sound intensity patterns. Then, a threshold value T can be obtained based on the experiments. Also, the sequences of sound patterns are also aggregated to reason whether a conversation is actually under way.

Formally, assume that S is a set of sound samples received within a time window. The Speaking Score ($\mathbf{S}$) is calculated as the ratio of high-intensity sound samples within time window. If the ratio exceeds ε, which is determined empirically, the time window is then classified as a chatting situation,

$$\text{Chatting Situation}(\mathbf{S}) = \begin{cases} 1, \text{Speaking Score}(\mathbf{S}) > \varepsilon \\ 0, \text{otherwise} \end{cases}$$

where Speaking Score (S) is determined by

$$\frac{\#\text{Magnitudes of Sound samples exceeds threshlod value T}}{\#\text{Sound samples in window time}}.$$

4) Zone Occupancy: To monitor the presence of caregivers, we deployed a mini LRF under the bed, which can scan the ward and report the number of people accurately in real time by calculating human legs. The details of human leg spotting algorithm are reported in [10].

IV. Evaluation

The proposed design is implemented and deployed in the ward no. 9A03 of NTUH. The sensor furnishing is implemented according to the principles and guidelines reported in Section III-B. The frequency of changing sensor location is relatively small, and changing battery frequently is an undesirable burden on medical workers. It is for these reasons that we utilized persistent power supply rather than using batteries for sensors. Before deployment, we collected a set of initial data and built a model to ensure the initial accuracy of situation inference. To obtain the initial data, we designed several scenarios that simulate realistic ADL in a ward. We also designed a user interface for labeling (see Fig. 4). The models are updated when a patient is discharged from the hospital.

A. Field Testing

The empirical field tests were conducted based on the four key situations of the system, namely, bed situations, bathroom situations, social situations, and the presence of caregivers. Five

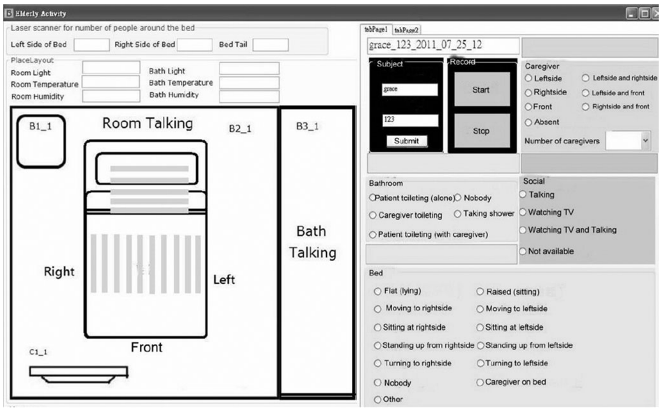


Fig. 4. Monitoring and labeling user interface.

TABLE I
RECOGNITION RATES FOR DIFFERENT SITUATIONS

Situations type	Precision	Recall
Bed situations/Lying on bed	0.9	0.95
Bed situations/Leaving bed	0.95	0.9
Bed situations/Turning over to the right/left	0.89	0.95
Bed situations/Sitting on bed	0.92	0.93
Bathroom situations/Flushing	0.81	0.95
Bathroom situations/Taking a shower	0.99	0.92
Bathroom situations/Speaking	0.93	0.95
Social/Watching TV	0.99	0.99
Social/Chatting	0.93	0.94
Social/Watching TV and Chatting	0.82	0.94
Zone occupancy/caregiver presence	0.93	0.92
Zone occupancy/caregiver absence	0.92	0.99

participants were all patients that took abdomen surgical operations and lived in the 9A03 smart ward for one week. The data for each experiment is of one-day quantity. It is worth pointing that it was hard to collect cases as each case occupied the ward for one week and not every patient agreed to participate in the experiment. In fact, it took more than three months to perform the complete experiments for five cases. Table I shows the results recognition for various situations, and the results are discussed in the following paragraphs.

As bed situations are mainly determined by k-means clustering and HMM, we ran several tests until suitable k was obtained. After setting each pressure vector into the corresponding cluster, a sequence of mapped cluster numbers was segmented into episodes. Each episode of cluster numbers was then further fed into HMM. The results shown in Table I indicate that our system can detect bed situations in high precision and recall rates when k is properly set.

The interested situations in the bathroom include taking a shower, flushing, and speaking. The humidity values grow rapidly after a person takes a shower. In this way, the system can determine the shower situations accurately (as shown in Table I). To identify the flushing situations, the system refers to a decision tree model supported by the readings of sound sensors, humidity sensors, and temperature sensors. The decision tree is designed so that it reflects the predetermined prior

TABLE II
SITUATIONS AND REACTIONS OF THE RABBIT APPLICATION

Situation	Reaction
Sleeping	The system automatically plays a music.
Sitting on bed	The rabbit performs a cheerful greeting.
Using walking cane	Step counts are shown at upper right corner.
Leaving bed	The rabbit reminds potential hazards and encourages the patient to do more exercise.

knowledge based on field observations. For example, the system detects a shower situation if the humidity and temperature values are higher than the threshold. On the other hand, the flushing situation can only be detected when both readings of sound sensors are high, and the temperature as well as humidity sensor readings are low. Also, the system can distinguish speaking and flushing situations based on the variation patterns of sound intensity.

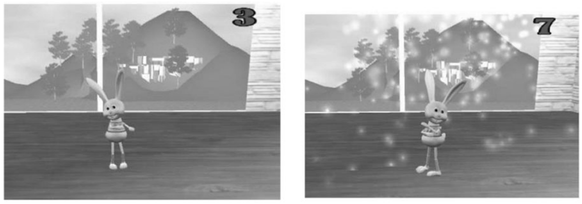
Situations for social engagement include watching TV and chatting. As mentioned, the act of watching TV can be detected based on the current sensor attached to the TV, whereas the chatting situation can be detected based on the speaking score (calculated using sound intensity values within a time window). Table I presents that the detection rates for social engagement situations are high during both watching TV and chatting. Note that the precision of "watching TV and chatting" is a bit lower than other situations, if the volume of the TV is turned too high, then sounds of the TV can be detected by the sound sensor and thus interfere with the calculation of the speaking score. Concretely speaking, it is hard to distinguish between sounds from TV and sounds generated from chatting by only using simple sound sensors.

Finally, zone occupancy situations were determined by LRF that scans and calculates the visitors' legs. To exclude the false positive cases, namely the cylinder-like objects, and false negative cases, such as the caregivers lying on the sofa, we employed a mention sensor to support the final decision. Most of the time, the patient was lying on the bed so that the legs detected by LRF should be of caregivers. Table I shows that both the precision and recall of the field tests are higher than 0.9.

B. Applications

On top of the system described in this paper, we have implemented and deployed two applications in the 9A03 ward.

1) Sward Keeper Rabbit: We designed a sward keeper rabbit application to interact promptly with the patients according to their situations (see Table II). The virtual character called sward keeper rabbit is designed to serve as an avatar of a caregiver. As shown in Fig. 5(a), the rabbit is counting the walking steps using a cane attached with an accelerometer. The number on the upper right corner shows the whole steps the patient has walked up. If the patient walks enough steps, then a firework animation will be played to praise the patient [see Fig. 5(b)]. In addition, we defined a collection of situation-action mappings so that the rabbit is able to react to the patient when a given situation is triggered. For instance, when the patient wakes up



(a) (b)

Fig. 5. Ward keeper rabbit application: (a) Executing counting task when an elder walks using the enhanced walking cane. (b) Firework animation used to praise the patient for reaching a predefined number of walking steps.

TABLE III
SUMMARY OF SATISFACTION ASSESSMENT

Question Item	Score
The system provides rich enough information for caring.	4.4
The system relieves my caring task burden.	4.0
The system can help me deliver more adequate care.	4.2
The system has no operational difficulties.	3.8
The user interface is satisfactory.	4.0
The system is ready for clinic use.	4.1
The system accurately reflects ward situations.	4.4
The system notifies dangerous conditions promptly.	4.1
The system relieves my caring task burden.	3.9
The system is ease to use.	3.8
The ward assists me so that patient needs are better satisfied.	4.2
The ward makes me aware of patients' recovering status.	4.4
The ward assists me in taking care of patients more efficiently.	4.3

*1:totally disagree; 5:totally agree.

and sits on the bed, the rabbit performs a cheerful greeting. Another example is that when the patient is leaving the bed, the rabbit softly reminds them of potential hazards (i.e., tripping) and encourages the patients to do more exercises.

2) Patient Situation Reporting: The second application is a patient situation reporting application used by the medical workers. Traditionally, a patient's activity level is evaluated daily and orally based on the Barthel index [12]. The medical workers pointed out that it is difficult for patients to recall precisely about their daily activities. Also, some patients tend to exaggerate their condition to get more social resources or attention. To provide objective and reliable observations, we built the patient activity report system to transcribe the collected situations into comprehensive reports of daily activities. By choosing a start and an end date, caregivers can also get a health report within a specified period. The report provides the following information.

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

2) *Sleeping and walking pattern 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 are separately shown in two histograms.

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

4) *Total social time:* the total time of the elderly people engaged in social-related activities.

C. Field Interview

After the applications were implemented and deployed, we conducted field interview to gather the qualitative opinion of our design. Nine patients (three male and six female) joined the interview session in total, each of them underwent a quarter-to-one interview process. The evaluating questions focussed on bed situations and the sward keeper rabbit application (reported in Section IV-B). To inspire the interviewees to think more about their real-life needs, we started the interviews with some sleep-related questions such as "Do you have the habit of taking a nap?" "In daytime, approximately how long will you spend on the bed?" and "what do you usually do on the bed in daytime?"

Next, we moved forward to the questions about the system. We asked, "Imagine that you wake up while nobody is around, does it seem attentive when the rabbit offers cheerful greetings to you though it is a virtual character?" Among all interviewees, five people liked the virtual character. "*It will be a wonderful idea if the rabbit can say something when I wake up, but it will be even more preferable if the rabbit has different greeting voices.*" (Female, 68s). Suggestions of providing additional information such as date and weather were also mentioned by the interviewees. The main reason that some interviewees did not like the virtual character was that it only greets instead of coming to their physical assistance: "*I would rather like the system that accomplishes what I really want when I get up, not just say hello.*" (Female, 65s). When the system detects that a patient is leaving bed alone, it sends out an alert to the nursing station. We found that all the interviewees agreed and looked forward to deploying such service in the wards. They pointed out the importance of such a reminder especially for those who suffer from dementia or Parkinson's disease. As for the design of "When the patient walks enough steps, then a firework animation will be played to praise the patient," six out of nine interviewees were fond of this service. They indicated the need of a virtual sports coach, "*I hope the system can help manage my exercise habit; for example, the system can encourage me to do more exercises and provide suggestions on how to do them appropriately.*" (Female, 73s). Also, many interviewees suggested that our system should be able to help improve their social connections, "*I hope the system can automatically help me contact my children when I get up*" (Female, 68s).

D. Satisfaction Assessment

To assess the satisfaction and usability of the patient situation, reporting application was (Section IV-B) built based on our system. As most of the users of the application were medical workers, we conducted a questionnaire-based survey of nurses and nurse practitioners in NTUH. The assessment targets were nine nurses and nurse practitioners. Interviewees were female between the ages of 28 and 33. The system was demonstrated to the interviewees individually (at most two) and then assessed to prevent mutual affection. The interviewers then delivered a questionnaire, which was about replying the extent of agreement

TABLE IV
COMPARISON OF SIMILAR PROJECTS

Name	Functionality	Sensor	Target	Place
Kautz *et al.* [13]	Reduce spatial disorientation	Ambient sensors	Alzheimer's patients	Home
Ganti *et al.* [14]	ADL monitoring	Wearable sensors & GPS	General users	Home and urban
Bardram *et al.* [15]	Medical task recognition	RFID	Medical workers	Hospital
Chen *et al.* [16]	Fall detection	Wearable sensors	Patients	Hospital
Tentori and Favela [17]	Urine monitoring	Weight sensors	Patients	Hospital (ward)
This work	In-ward ADL monitoring	Ambient sensors	Patients and caregivers	Hospital (ward)

*ADL=activities of daily living.

toward each proposition, relating to the individual applications. The assessment results of agreements on propositions are listed in Table III. The numeric score is averaged over all collected questionnaires. To make it clear, 1 and 5 points represent total disagreement/agreement, while other points reflect the corresponding degree of agreement. Except some question items, most of the assessment results reflect general agreement on system application usability. The propositions in the questionnaire are designed to elicit the degrees of satisfaction of the application and services. So the results imply a higher degree of compatibilities to user needs when compared to other real-world research projects such as Bricon-Souf and Newman [4].

E. Lessons Learned

Valuable lessons and experiences have been acquired in this research. Many unexpected issues emerged after the system was deployed and operated in the field. The lessons learned are detailed below.

1) Dealing With Social Issues: The relationships among the research team and medical staffs should be strongly connected throughout the research process. Opinions interflowed within intercross meeting should involve system goals, deployment policies, collaboration approaches, and experimental procedures. We began to hold a monthly meeting with medical staffs and psychology experts in early stages so that design considerations that are easily ignored by the system developers may be recovered by domain experts. For instance, "labeling for the ground truth" is important for most supervised classification algorithms, but medical staffs suggest that it is hard to perform such procedure, as it is a heavy burden for caregivers. Such real-world domain knowledge is so important that it makes some recognition algorithms infeasible. We also observed that most patients and their caregivers trust their attending physician. If the attending physician understands how the research can help the patients and convey this idea to them, then the patients tend to be friendlier to the research team.

2) Dealing With Limited Deployment Time: As mentioned, most hospitals are typically of high occupancy rate. There is little time for setting and resetting a used ward. Before starting to construct sensor modules, it is important to measure and record the layout of the ward, including the window places and sizes, the position of the power supply. Taking pictures of key deployment area is also helpful. When resetting the system for the next patient, system maintenance and sterilization of the ward must be performed in parallel within few minutes, so that modular and loosely coupled design of both hardware and software are preferred.

3) Dealing With Sensor Malfunctioning: In practice, sensors can fail in many unexpected ways and need to be repaired or replaced constantly. Unfortunately, few patients and caregivers allow system developers to enter the ward and diagnose the failure. Thus, we suggest the requirement of at least some basic fail detection mechanisms to pinpoint the failures remotely. For example, we configured the sensors to send the heartbeats periodically. Redundant sensors are also useful for recovering the system without distributing the personnel of the wards.

4) Dealing With Noises Derived From the Environments: Situation inference can be inaccurate due to the noises derived from the environments. For instance, due to poor sound insulation, the sensor for analyzing flushing sound not only collects the sound from neighboring wards but also collects the sound from the nearby aisle, thus corrupting the recognition accuracy. We suggest that we find out the potential source of noise carefully, and then use different types of sensors to enhance the robustness of results. For example, we introduced two motion sensors so that the recognition module only activates when someone is entering the toilet.

V. RELATED WORK

Several pervasive healthcare systems have been proposed to improve the quality of lives of the elders. The aware home is a pioneer of pervasive healthcare systems [18], which focuses on devising assistive technologies based on context-aware and pervasive technologies. The assisted cognition project [13] explores the usage of AI techniques in supporting independence and life quality of Alzheimer's patients. Researchers in this project used pervasive sensors to reduce spatial disorientation of the patients. SATIRE [14] is an assistive living and residential monitoring system that utilizes sensor data sent from wearable devices and performs activity recognition. These works laid a solid technological foundation for the pervasive healthcare research. However, they were deployed and tested in a controlled environment.

So far, there are relatively few attempts to design pervasive healthcare systems. Bardram *et al.*'s team is one of the pioneers. They presented the design principles for applying context-aware computing in a hospital and further shared the experiences coming from a real-world deployment of pervasive technologies in a hospital environment [15]. They also proposed three issues when deploying pervasive healthcare systems in the field: hardware, software, and user setting [19]. Our work differs from Bardram *et al.*'s work in that Bardram *et al.*'s observed subjects were medical staffs whereas in our work the observed subjects were patients. The context recognition of their work is semiautomatic in the sense that the medical staffs have to proactively report their activities and intentionally approach the RFID readers. Using wireless weight sensors, Tentori *et al.* constructed and deployed an automatic urine monitoring system. When the weight reaches a threshold, nurses will be informed through the smart phone [17]. Some studies have been made on detecting human activities in a hospital, most of them focus on determining emergent situations such as fall detection [16]. Table IV summarizes the key features of related projects. Our work is unique in that the proposed system is able to monitor ADLs of unusual targets (patients) in an unusual place (wards in a hospital). As shown in the preceding sections, autonomous and continuous ADL monitoring in such environments is challenging and requires extensive design and deployment efforts.

VI. Conclusion

Deploying pervasive systems in a real-world environment is still very challenging today. This paper reports the lessons learned from engineering a pervasive healthcare system in a real-world smart ward. The major motivation of this research is to understand and to bridge the gap between an in-house pervasive healthcare system prototype and a long-running real-world system. To ensure the system functions align with the most urgent needs, we conducted a field survey in a complete nursing process to probe for the real needs. We found that bed, bathroom, social, and presence of caregivers are the most critical situations that the medical workers desire to know. By considering several practical issues, we designed furnishing and situation inference mechanisms. After that, we built and deployed a pervasive healthcare system with two applications. In the qualitative interview, the applications are proven helpful for the medical workers. This study should provide a descriptive basis for further research. There is a continuing need for new pervasive applications in the hospital. For example, monitoring the exhausted status of intravenous drip is desirable in the ward. Also, monitoring the medicine intake of patients is helpful for caring the patients.

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