

Towards an Evidence-Based and Context-Aware Elderly Caring System Using Persuasive Engagement

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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, long-term healthcare is labor intensive. To alleviate the possible social costs associated with manpower and physical resources, we propose an evidence-based caring system which can inconspicuously and automatically monitor the health status of the elderly by continuously analyzing their real-life long-term living patterns deduced from activity recognition. In this way, caregivers can get hold of the behavior changes even the elderly is not under caregivers' supervision. Moreover, we adopt a persuasive policy to provide timely reminders and encourage the elderly to achieve a healthier life. In the primary stage, we do preliminary experiments in a nursing room. Based on the experiment, we conduct several interviews aiming to improve our system in the next phase.

Keywords: Context-aware, persuasive technology, elderly healthcare.

1 Introduction

Aging population is a critical global issue. Evidence [9] shows that approximately 10 percent of the world's population is over the age of 60, and the proportion will have doubled by 2050. By 2010 United Nations for Human Rights claimed that aging population has become a national issue rather than merely local problems. An increasing number of countries have been attaching importance to establishing the well-being of the elderly. To alleviate the possible social costs associated with manpower and physical resources, it is necessary to develop assistive technology to help elderly people live independently.

Knowing the activities of daily living (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. Without objective evidence from other sources, medics have to completely trust the reports. Such a problem obstructs the medics from knowing the real situation about the elderly. This motivates us to design an *evidence-based report system* to automatically collect and analyze daily living data of the elderly. In addition, with

limitations in manpower and available resources, it is hard to ask caregivers to attend the elderly all the time. To resolve this difficulty, we design a virtual caregiver which can timely remind and encourage elderly people. The actions and reminders of the virtual caregiver are one metaphor of the caring behavior of a human caregiver.

Since our system is now in the primary stage, the setting of our evaluation focuses primarily on a bedroom-scale environment. We perform preliminary experiments in National Taiwan University Hospital and set our target activities of the elderly at *Sleeping, Sitting, Leaving Bed, Interactions with caregivers, and Using Walking Cane*. Instead of purely focusing on technology, we attempt to acquire the true feelings of the elderly when they interact with our system. Hence, we conduct several interviews aiming to acquire directions and suggestions for the improvement in the next stage.

2 Methodology

The framework of the entire evidence-based and context-aware healthcare system is shown in Figure 1. An inhabitant interacting with the ambient intelligence (AmI) enhanced environment is not only a sensing data producer but also a service consumer.

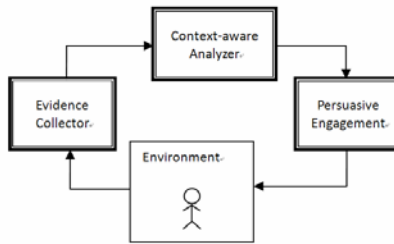


Fig. 1. The proposed evidence-based and continuous health improving framework

One's ability to perform activities of daily living (ADL) can be used to document some health related statuses. For instance, an abnormal living pattern may reveal some physical or mental problems. In our framework, *Evidence collector* truthfully collects each daily living clue of the inhabitant; this can be achieved 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, *Context-aware analyzer* outputs meaningful features based on the information from *Evidence collector*. 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 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.

2.1 Current Implementation

As one realization of the continuous health improving framework, in the primary stage, we implement a healthcare system for the elders in a bedroom as shown in Figure 2. For the *Evidence Collector*, we create non-obtrusive sensing module to collect clues regarding ADLs when the elderly people interact with the ambient sensors. Sensory data will first be translated by the *Raw Data Analyzer*, the first component in *Context-aware Analyzer* into features. Feature data will then be fed into two-layered *Activity Recognition Engine*.

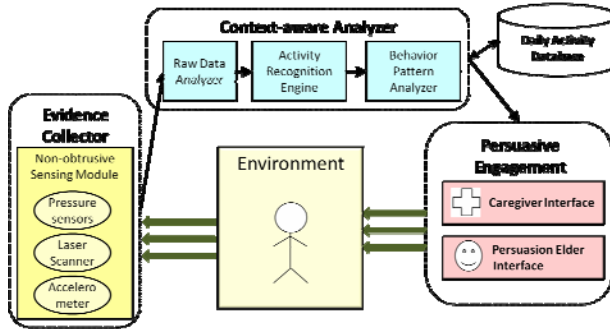


Fig. 2. Implementation architecture in current phase

High-level activity data will be further analyzed by *Behavior Pattern Analyzer*, which is the last component in *Context-aware Analyzer*. Living patterns such as the total sleeping time or the number of leaving bed within a specified duration will be discovered by the *Behavior Pattern Analyzer*. All the living data will be stored in *Daily Activity Database* so that caregivers can access historical living data in the past. There are two user interfaces in *Persuasive Engagement* module. For the caregiver, system automatically generates health report about the elders. And for the elders, system will timely encourage or remind them in some situations which can be detected by *Context-aware Analyzer*. Evidence shows that the sleeping patterns are important both in physical and mental aspects for the elderly [6][7]. Poor sleeping patterns are usually comorbid with medical illness and are associated with increasing risk of morbidity and mortality [6]. In addition, it has high risk of tripping when the elder is getting out of bed [7]. Therefore, we choose five activities which are *Sleeping*, *Sitting*, *Leaving Bed*, *Interactions with caregivers*, and *Using Walking Cane*.

2.2 Non-obtrusive Sensing Module

Our non-obtrusive sensing module inconspicuously collects all clues about how and when an elder interacts with his/her surrounding objects. The term *non-obtrusive* here means not interrupting the daily task of an elder. We choose three non-obtrusive sensors in our system: pressure strap, accelerometer, and laser scanner. We use the *NTU Taroko* node as the wireless sensor network (WSN) node and each of them can connect to pressure straps and accelerometers using a sensor daughter board. In Figure 4 (b), one accelerometer has been connected to one *NTU Taroko* node, which has been

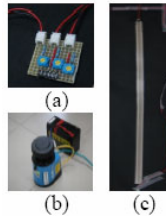


Fig. 3. (a) A pressure daughter board. (b) A Laser Range Finder. (c) A pressure strap.

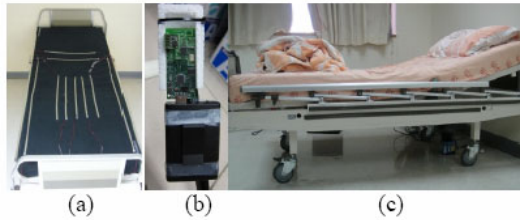


Fig. 4. (a) Deployment of pressure mat. (b) A *NTU Taroko* node connects to an accelerometer and a battery box. (c) Snapshot of our deployed sensing bed. The LRF is put beneath the bed and the pressure sensor mat is covered by the bed sheet.

connected to the battery. An accelerometer is attached to a walking cane, which can be used to detect the walking state (e.g. walking pace) of the elderly.

Pressure sensors have been used in a smart environment to monitor the elders in many ways since these sensors are among the most inconspicuous ones which can be seamlessly attached to the furniture or on the floor [2]. As for bed-related activity monitoring, various layout formats of pressure sensors have been tested to compare monitoring performance. For example, previous work [1] weaved 336 circular pressures into the bed mattress. Since these pressure sensors resulted in a large feature set (336 features in their work), they took advantage of Principle Component Analysis to reduce its feature dimension. Though they achieved promising accuracy rate, the labor power and power usage for later maintenance is costly. Therefore, we try to strike a balance between the manpower of maintenance and the activity recognition accuracy. We conducted pilot trials on sensor deployment and finally determined deploying eleven pressure straps on a single bed. The deployment is shown in Figure 4(a). Briefly speaking, we segment the bed into four parts, which are shoulder part, waist part, left edge part, and right edge part respectively.

Owning to the fact that a pressure mat can only detect on-bed activities, the Laser Range Finder (LRF), shown in Figure 3(b) is incorporated to provide location information about persons surrounding the bed, including both the elder of interest and his/her caregivers. Previous work used a camera to monitor situations around the bed [3]. Though visual systems can give rich information regarding human postures, it may violate one's privacy which is crucially concerned in a bedroom. Moreover, when inhabitants sleep or take rest, they tend to turn off the light. Unlike visual system, the performance of LRF won't be affected even under low illumination. Therefore, we adopt our prior work [4] and do human detection in the vicinity of the bed by LRF.

2.3 Raw Data Analyzer

A *Raw Data Analyzer* preprocesses sensory data into higher-level contexts (or features) according to the characteristics of each sensor. For pressure straps, each sensor reading will be discretized into binary state $\{On, Off\}$ based on pre-defined thresholds; raw data receiving from the accelerometer will be analyzed by observing the pattern of square sum of all axes value; the result is used in detecting human walking activity. Lastly, for the LRF, aiming to do the path tracking, candidate human coordination detecting from laser sensors will be translated into location grids shown in Figure 5. The area label $L1$ stands for the first (nearest) area in the left side of the bed. Segmenting the areas according to the distance helps in considering temporal movement of a person. For instance, caregiver coming from outside the room may cause a sequence such as $\{L2, L1\}$.

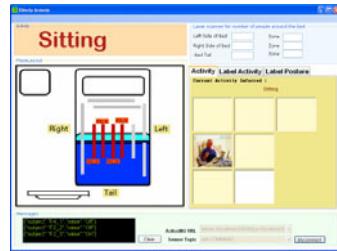
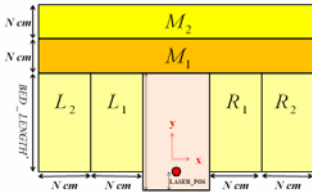


Fig. 5. Location grid layout for our location feature

Fig. 6. Monitoring interface for caregiver

2.4 Activity Recognition Engine

The aforementioned Analyzed contexts will be further fed into our Bayesian network inference model. The model adopts a two-layered structure so as to achieve a higher accuracy rate since some noisy sensor data will be filtered out after the first-layered inference task. We use open-sourced WEKA [5] as a tool to implement our activity recognition engine. The pressure state and accelerometer contexts coming from the *Raw Data Analyzer* are the inputs of the first layer engine which is used to infer primitive actions of activities. The engine is a multi-class Bayesian network model which estimates five class labels, including *Sitting on Bed*, *Lying on Bed*, *Sitting near Right*, *Sitting near Left*, and *Walking Step*. We name the output (estimated) label of the first layer *action*. The estimated *actions* will be further fed into the second-layer inference stage. The second-layer stage is composed by six individual spatiotemporal Bayesian models, each of which represents one of the target activities included *Sleeping*, *Sitting*, *Leaving Bed*, *Interactions with caregivers*, and *Using Walking Cane*. Since an activity may be comprised of a sequence of actions. For instance, the *Leaving* activity consists of an action sequence such as $\{Sitting\ on\ Bed \rightarrow Sitting\ near\ Right, Sitting\ near\ Right \rightarrow R1\}$ (please refer to Figure 5). Hence, we take also these temporal features into account both in the training and testing phase. Whenever a sequence of actions occurs in a predefined time window, these actions will be composed and formed up a new temporal feature. Figure 6 demonstrates the monitor interface for the caregiver. The

red straps on the bed figure are represents those pressed pressure straps. The red word shows the on-going activity inferred by our system is *Sitting*.

2.5 Behavior Pattern Analyzer and End Persuasive Engagement

Each inferred activity will be stored in a database and fed into *Behavior Pattern Analyzer*. Firstly, successive and same activity records will be aggregated into one episode. The starting time and the length of one episode will be recorded. Secondly, expert domain knowledge from the geriatrics is used to diagnose whether there exist targeted activity patterns. If such pattern appears, system will promptly interact with the elder people using persuasive strategy. Moreover, a health report for caregivers will be automatically generated. Therefore, caregivers can capture the evidence-based activity report of the elder regardless human supervision. Details of persuasive engagement component are depicted below.

Persuasive and Reminder System for Elderly. Aiming to support appropriate assistance for the elderly people, we design a persuasive and reminder mechanism to promptly interact with the elderly based on their on-going activities. To make the interface much more attentive, we create a friendly social agent, *Home Keeper Rabbit*. The animations and voices of the *Home Keeper Rabbit* serve as the avatar of a given caregiver. The *Home Keeper Rabbit* shown in Figure 7(a) 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 7(b)) and cheer on the elderly to exercise as much as possible.

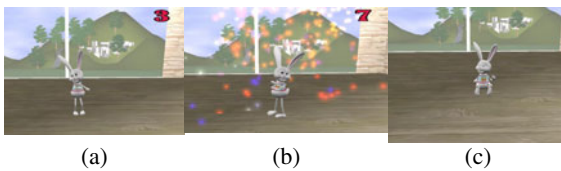


Fig. 7. (a) The *Home Keeper Rabbit* is executing counting task when an elder walks using the enhanced walking cane (b) Firework animation used to praise the elderly for reaching a predefined number of walking steps. (c) The animated rabbit sits when the elderly is sleeping.

Table 1 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. 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 which are *walking duration* and *sleeping duration*. Table 2 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.

Table 1. Timely reminders or encouragement for target activities

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

Table 2. Persuasion policies supported for interested activity episode

Activity episode	Description of system feedback
Sleeping	When an elderly sleeps more than one hour in the <i>daytime</i> , the <i>Home Keeper Rabbit</i> 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. <i>Home Keeper Rabbit</i> encourages the elderly when the elderly reaches a higher level

Evidence-based Health Report for Caregiver. As for realizing an evidence-based report system, we worked closely with some medical researchers from National Taiwan University Hospital and 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. We further design a website as a personalized healthcare portal (or *Help Center*) for the caregivers to help themselves easily get health reports via the Internet. Figure 8 shows the front page of the Help Center.

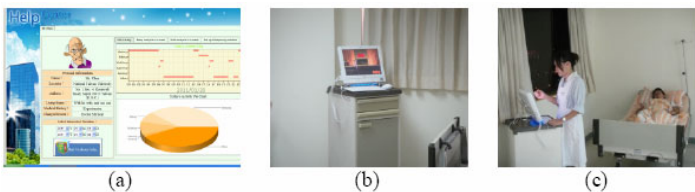


Fig. 8. (a) The front page of the evidence-based health report website. (b)(c) Scenarios of our proposed system in practical use.

Available information provided from this portal is as follows:

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 its time instances in the past one week are rendered as a point map.

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

3 User Study

What the elderly really think should be the core guidelines for any researches on eldercare. Instead of purely focusing on technology, we also attempt to acquire the true feelings of the elderly when they interact with our system. We do several interviews to collect suggestions from some seniors. Due to the limitations of the environment setting, we took a video to demonstrate a potential application of our system. We carry a notebook and play the video to interviewed seniors who we met in a public place. The video serves as an inspiration for the seniors to reflect upon their real-life needs through the proposed technologies.

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.

3.1 Participants

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.

3.2 Feedback of the Persuasion Mechanism

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?”, “In 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 like 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 owing 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 doing an excess of exercise; besides, I need encouragement to do more exercise via appropriate suggestions.” (Female, 73s, Hospital volunteer)

3.3 Discussion

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 can 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.

4 Conclusion

In this work, an evidence-based caring system along with a persuasion strategy is proposed. To generate an evidence-based health report regarding an elderly, we seamlessly deploy ambient sensors in a context-aware environment and recognize the on-going activities based on these sensed data. Such an inconspicuously monitoring system lessens the labor manpower for the caregivers since they do not need to constantly supervise the elderly. Moreover, some behavior changes reveal the potential health problem; therefore, we can collect long-term data such that an abnormal behavior change can be detected as early as possible. In addition, to promptly give appropriate assistance to the elderly, we design a virtual agent who can interact with the elders based on the on-going activities. We have conducted pilot experiments in a nursing room and proceeded several in-depth interviews based on the results of our current system. Future directions towards the next-staged system have been derived from these interviews and we can continuously enhance our system based these valuable suggestions.

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