Human-Centric Situational Awareness in the Bedroom

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Abstract. Bed-related situation monitoring is a crucial task in geriatric healthcare. Due to shortage of qualified caregivers, automatic detection of the situation in a bedroom is desirable since risks may arise when an elder gets up from the bed alone. In addition, analyzing the total amount of care time of an elder is helpful when the social effect on the improvement of the elder's health needs to be evaluated. This paper presents a context-aware healthcare system which makes use of multi-modal and un-obtrusive sensing technology meanwhile taking human feeling into account. Specifically, we choose ambient sensors such as pressure straps and a laser scanner to monitor both the activity of the elder and his/her surroundings. Moreover, a context fusion is further proposed to infer the situation of the elder. Experimental results demonstrate the high promise of our proposed methods for bed-related situation awareness.

Keyword: Context-aware, situation awareness, multi-modal sensor fusion.

1 Introduction

Situation monitoring is a crucial task when the elderly people living alone or being unsupervised. Due to shortage of the qualified caregivers, an assistive eldercare system will be helpful for alleviating the pressure from these caregivers. Evidence shows that the risk of tripping is high especially when the elder is getting out of bed [1]. Moreover, dizziness condition may be introduced when the elder sitting up on the bed from a lying position. In addition to detecting different actions on the bed, monitoring the situations in different close-by areas around the bed is also important. For instances, the total caring time of caregivers coming around may indirectly reveal the mental health of elderly people. Therefore, we propose a human-centric situational aware system which targets at detecting five on-bed and bed-side activities including *Sleeping, Sitting, Leaving Bed, Caregiver Around* and *Walking.*

In order to detect the undergoing activities of an elder, sensors are chosen and deployed according to the scenarios relevant to the activities. Generally, ambient sensors have been involved in recognizing bed-related situations in many researches [3, 4]. Such ambient sensors will bring the least disturbance to the original life of the elder when being compared with the wearable sensors. Therefore, we choose ambient sensors and deploy them to detect the activities of interest in this work so that the elder

B. Abdulrazak et al. (Eds.): ICOST 2011, LNCS 6719, pp. 72–79, 2011.
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can proceed with those activities just like before, i.e., without any interruption. Among these ambient sensors, pressure sensors are the most inconspicuous ones since they can be laid out in any appropriate format suitable for serving as a sensing mat for bed-related activity detection. In order to make the implementation more practical, we try to lessen the sensor cost and the deployment labor while maintaining the sensing accuracy. After several pilot experiments, we finally decide to employ 11 pressure sensor straps to form the sensing mat for a single bed.

Due to the fact that a pressure mat can only detect the pressing actions performed on a bed, we further incorporate a laser scanner beneath the bed for detection purpose so as to tell whether the elder or the caregivers are around the bed. Specifically, we analyze the distance-angle readings of the laser scanner and categorize each reading into its corresponding area according to the translated coordinate of detection outside the frame of the bed. Now, in order to fuse the data from the laser scanner and the pressure sensors, a spatiotemporal Bayesian classifier serving as a high-level data fusion engine is designed to infer bed-related situations. To achieve higher accuracy of the inference task, we also take the temporal relationship among all sorts of extracted features into account.

2 Related Work

Numerous researchers have conducted bed-based sensors to analyze bed-ridden behaviors and gave automatic assistance to the elders according to the analysis. Seo [3] *et al.* proposed an Intelligent Bed Robot System (IBRS) which equipped two robot arms and a pressure sensor mattress on a special bed for assisting elderly people and the disabled. Focusing on monitoring situations of the elders around the bed, Weimin *et al.* [2] weaved 7x7 circular pressure sensors and eleven pressure sensor straps to detect the user's movement on the bed. Although they acquire good performance in classifying targeted situations of the elders, the sensor deployment is still too costly. Besides pressure sensors, they incorporated camera for sensor data fusion. Despite that the visual system can obtain rich information on human postures, the involved computational complexity is quite high and its performance is varied with the camera settings of as well as the environment (such as different view-angles of the camera and different illuminations). Moreover, the privacy issue of using a camera might be a critical concern for an elder or a patient. In the work [5], wearable sensors such as ultrasounds, RFIDs, and accelerometers were used to detect dangerous situations for the elders. However, the wearable sensors are generally considered inconvenient for practical use.

In order to propose a more human-centric smart bedroom, our work focuses on using *non-obtrusive* sensors such as pressure straps and laser scanner to recognize bed-related situations. The meaning of the term "*non-obtrusive*" refers to a description indicating that the elderly people are not disturbed both physically and mentally. These non-obtrusive sensors hereby will be deployed seamlessly in the environment and all together provide the contexts about activities performed by the elders.

3 System Architecture

In this section, we provide an overview of the proposed human-centric situational aware system. We choose *non-obtrusive* sensors with multiple modalities for the reason mentioned previously. Moreover, since sleeping and taking a rest are the major activities in a bedroom and these two activities often proceed under very low illumination, which may render the use of camera even more non-preferable. Therefore, a laser scanner or extensive floor pressure sensors will be adopted for detecting users' current locations. Given this thought about sensor arrangement, a more human-centric environment can be created.

Rather than use the received sensor's raw data directly, we hereby interpret every sensor reading as a high-level feature. Biswas *et al.* [7] defined a *micro context* as a fragment of information about one user and his/her activity related contexts. For instance, they took activity primitives as the *micro contexts*. They found that *micro context* information gives better recognition assistance than low-level sensor feature. By borrowing their concept, we therefore, define two types of *micro contexts* in our work here, namely, *bed-related micro contexts* and *location micro contexts.* Since a bed is often the major object in a bedroom, the bed-related activities will be our main focus. In this paper, *bed-related micro contexts* will be jointed with *location micro contexts* for further co-inference. The multi-modal *micro contexts* are fed into a classifier to infer the current situation. Moreover, some activities are inferred by considering the temporal relationships among various *micro contexts*, including *bed-related* and *location micro-contexts.* All these temporal features are learnt in the offline training phase and will be incorporated into our activity models.

4 Methodology and System Implementation

In this section, we introduce our system implementation. We choose pressure straps as the bed-based sensors which are attached to the mattress ticking and a laser scanner as the location awareness sensor. Next, we provide more details on how the system is implemented.

4.1 Bed-Related Micro Context Extraction

The *bed-related micro contexts* are acquired by analyzing the readings of pressure straps deployed on the bed. We use wireless sensor network nodes to receive and send sensor messages. We apply event-driven mechanism in sensory data transmission, which means the node sends out a packet only when the difference between the current and the previous readings exceeds a predefined threshold. Each received sensor reading will be converted into binary state based on a predefined threshold T. Both the threshold value of the difference of successive readings and the cut point for binary states converter are acquired from experiment results.

As for the process of inferring the current *bed-related micro contexts,* we first observe the primitive postures of the elder on the bed corresponding to different targeted situations. After some experiments, we found that four primitive postures will be sufficient to classify every situation we interested in. Therefore, we take each posture as one *bed-related micro context* and annotate it using one label from {*Lying on Bed, Sitting on Bed, Sitting near Right, Sitting near Left*}. Unlike most of the prior works making use of all sensors deployed on the bed to detect the current posture of the user, we segment the bed top into four meaningful regions, each of which covers a group of

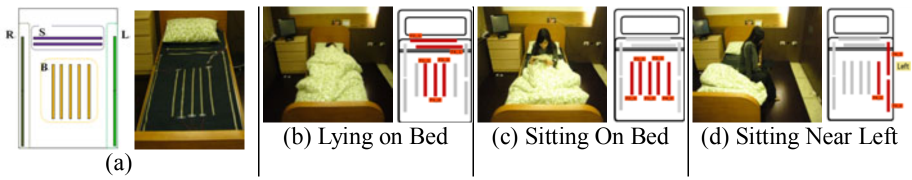


Fig. 1. Image of our bed deployment and three snapshots of pictures and their corresponding monitoring interface

pressure sensors. These regions are namely ***R**-Right Side, **S**-Shoulder Part, **B**-Lumbar-Hip Part, and **L**-Left Side,* and each group of pressure sensors takes charge of providing some *bed-related micro contexts*. Note that the ***R**-Right Side* sensor group and the ***L**-Left Side* sensor group are deployed to detect whether the user is sitting near the long bed edges, whereas the sensor group over the ***S**-Shoulder region* is crucial for the detection of "*Lying on Bed*" posture since empirical evidence indicates strong correlation between the nontrivial shoulder pressure and the "lying down" posture. In ***B**-Lumbar-Hip region*, we put five pressure sensor straps, all separated by some distance and laid out in parallel to the long bed edges, mainly in the proximity of the bed's middle so that we can reason the direction the user is moving in laterally by analyzing the state changes over the five pressure straps. Figure 1(a) shows the layout of our pressure straps deployment.

Table 1. Partitioned rule-based bed-related micro context inference mechanism

Bed-related Micro Context Processing algorithm

Initialize L_n, S_n, B_n, and R_n to 0.
Initialize all *part vectors* to default condition (each element is in "*Off*" state).
while a new *event vector* is received
    Update the corresponding *part vector* according to the pressure ID of the *event vector*
    Recalculate and update *part vector*
    if $S_n > 0$ ***and*** $B_n > 1$
        micro-context := *Lying on Bed*
    else if $S_n = 0$ ***and*** $B_n > 1$
        micro-context := *Sitting on Bed*
    else if $S_n = 0$ ***and*** $B_n < 4$ ***and*** $R_n > 0$ ***and*** $L_n = 0$
        micro-context := *Sitting near Right*
    else if $S_n = 0$ ***and*** $B_n < 4$ ***and*** $L_n > 0$ ***and*** $R_n = 0$
        micro-context := *Sitting near Left*
end while

Two types of feature vectors for the pressure sensors are used in the system. The first type is an *event vector* which contains only the currently received pressure strap ID and its converted binary state. The other type is a *part vector* which contains all pressure states of the sensor group covered by one region (Refer to Fig. 1(a)). The *part vectors* will continually update states over time. As mentioned, we create a *part vector* for the group of pressure sensor straps for every region. For instance, the *part vector B* at time *t-1* is {*On, On, Off, Off, Off*}. If the leftmost sensor of part *B* is changed to "*Off*" at time *t,* then the *part vector B* will be updated to {*Off, On, Off, Off, Off*} at time *t*. Thus, the system can forward all the most up-to-date *part vectors* into a *partitioned rule-based inference mechanism* to infer the *bed-related micro contexts* using the algorithm shown in Table 1. There are four variables L_n, S_n, B_n, *and* R_n indicating the respective numbers of the pressed sensor straps within the sensor group covered by respective regions.

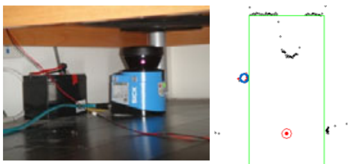
4.2 Location Micro Context Extraction

The source of a *location micro context* originates from the laser scanner. The LRF is placed on the floor beneath the bed closer to the headboard. Figure 2(a) shows the arrangement of the laser scanner used in this work. The blue circle in Fig. 2(b) points out the possible coordinates of a possible caregiver nearby the bed.

In order to track the caregivers around the bed and distinguish their movement paths, we further translate the possible users' coordinates into *location micro contexts* based on their distances vs. their nearest bed edge. In preliminary phase, we simply segment the area around the bed into six sub-regions as shown in Fig. 3. For location estimation, we use the Cartesian coordinate system and set the laser position as its origin represented as a red circle in Fig. 3. Different sub-regions have different distances to the bed. Experimental tests indicate that the mean distance between a caregiver and the bed edge is within 1 m; besides, we observe that the caregivers are accustomed to stand in the two sides of the bed rather at the tail of the bed, which reminds us that we should segment area nearby the tail of the bed into another sub-region. With all these segmented sub-regions, a *location micro context* can be represented by an *area label*. A sequence of *area labels* reveals the temporal path of a caregiver or the elder. For example, a caregiver approaching the bed may lead to the *area label* sequence {R_2, R_1}, whereas the other sequence such as {R_1, R_2} may imply the activity of a user, elder or caregiver, is leaving from the bed.

4.3 Temporal Feature Handling and Situation Awareness

After gathering *bed-related micro contexts* and *location micro contexts*, we then fuse these two micro contexts to infer if one of the five targeted bed-related situations occurs. First, we learn the temporal features from training data for each situation. We run *Temporal Feature Test* for each situation which automatically finds whether a situation contains *n-gram temporal features* from the training data. In this work, we prefer to use *two-gram temporal feature* for problem simplification. That is, a *two-gram temporal feature* is composed of successive state changes of two different *micro-context*s within a specified time window for the same situation. Take the {*Leaving*} situation as an example. One may shift one's center of gravity from the bed's middle towards one side of the bed, and then put his/her feet down on the ground. In such case, the *Temporal Feature Test* will find two two-gram *temporal features* which are {*Sitting on Bed*$\longrightarrow$*Sitting near Right*} and {*Sitting near Right*$\longrightarrow$*R1*}. Since we adopt the event-driven data transmission strategy, the time window for detecting a temporal feature is defined by the number of state changes rather than by the interval of the time window. We predefine the length of time window *W* to test whether there exists any temporal feature in a situation. If two successive state changes of different



(a) (b)

Fig. 2. (a) Laser Range Finder put under the bed. (b) Candidate human detected

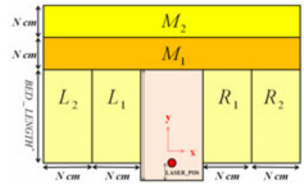


Fig. 3. The sub-regions of the area around the bed (N=100 in our work)

micro contexts occur within the predefined time window, we combine the two *micro contexts* and introduce a new *temporal feature* for that situation. After composing temporal features for each situation, we apply WEKA [9], an open-source Data Mining Software in Java, to build five Bayesian Network models, each of which represents one situation of interest. Before the model training, we pool training data into the Attribute Selector (also supported by WEKA) which runs the Best First search algorithm to choose all relevant features corresponding to each situation. After selecting the relevant feature sets, we build up five independent Bayesian models, one for each situation, based on the chosen features. The five models will be further used in testing phase to infer the current situation. The feature set obtained in testing phase is expressed as f_t= $\{BM_t, LM_t, TF_{\sim t}\}$ where BM_t is the *bed-related micro contexts* inferred at time t and LM_t represents the interpreted *location micro contexts;* $TF_{\sim t}$ is temporal feature sets composed within the interval [t-W, t] where W is the predefined time window. We take f as observation and feed it into the trained Bayesian models corresponding to each interested situations. After calculating the probability of each model given f, the situation whose probability exceeds the threshold value will then be regarded as the one which is taking place at time t.

5 Experiments and Results

We run a pilot experiment in NTU INSIGHT OpenLab, an experimental space aiming to support research on smart home. Three participants are recruited to test the feasibility of the work; one is female and the other two are males. Their heights range from 160 to 183 cm and the weights ranging from 47 to 63 kg, respectively. The bed size is 200cm×66cm and the pressure strap is 62 cm long. All sensor signals are wirelessly transmitted. Though there is significant difference between heights of the three participants, the pressure straps put under the shoulder part can detect almost every "lying down" action. The evaluation of our *bed-related micro context* is shown in Table 2. The confusion matrix shows the high accuracy rate in each *bed-related micro context*. Some misclassifications occur when the participant sits in the middle of the bed but put his/her hands near the pillow. The hands may trigger the *Shoulder Part* pressure sensors and mislead S_n to become a positive number. Consequently, *Sitting on Bed* will be misclassified as *Lying on Bed*.

Table 2. Confusion matrix for bed-related micro context inference

		Detected bed-related micro context			
		Lying on Bed	*Sitting on Bed*	*Sitting near Right*	*Sitting near Left*
Ground Truth	*Lying on Bed*	100%	0%	0%	0%
	Sitting on Bed	5%	94.3%	0.4%	0.3.%
	Sitting near Right	0%	14.6%	85.4%	0%
	Sitting near Left	0%	9.3%	0%	90.7%

Table 3. Detection accuracy for five situations

	Sleeping	Sitting	Caregiver Around	Leaving	Walking
Precision	91%	99.2%	98%	97%	100%
Recall	100%	95.6%	85%	89%	81%

Another misclassification occurs when *Sitting on Bed* is falsely identified as *Sitting near Right/Left*. Such misclassification is caused by the structure of the bed. The distance from the top of bed to the ground is only about 35 cm, but the shank length of our tallest participant's is about 45 cm. Therefore, all of the *Right/Left Side* pressure sensors will not be triggered when this participant sits near either side of the bed. It violates our rules of R_n >0 or L_n >0 and make the final classification as *Sitting on Bed*. This motivates us to establish more user-independent rules to increase the overall robustness. With the *bed-related micro contexts*, we next derive the *location micro contexts* from the laser scanner, and then run *Temporal Feature Test* to find temporal features for every situation. After composing temporal features by analyzing the training data, we train Bayesian models offline for each situation and apply the Attribute Selection in WEKA. The experimental result is shown in Table 3. For situations *Sleeping*, *Sitting*, *Caregiver Around*, and *Walking*, precision and recall are calculated based on every feature set *f* defined in section 4.3. For the situation {*Leaving*}, it is difficult to define the starting point of the "*leaving bed*" activity. Therefore, we define a true positive as successful detection of the event where a user completes the entire leaving bed activity. From the result, precision of {*Sleeping*} is influenced by the {*Caregiver Around*} because the laser scanner missed some information of the caregiver. We analyze potential disturbance and found out that the structure of our currently selected bed limits the detection ability of the laser scanner for the reason that the lowest frame of the current bed is not 40 cm high, which is the least height for normal leg detection using laser scanner according to our prior work [6].The situation {*Sitting*} will be confused with the situation {*Sleeping*} if the user put his/her hands near the pillow.

7 Conclusion and Future Work

In the paper, a multi-modal sensing and high-level context fusion strategy are proposed to detect bed-related situations. We choose pressure sensor straps and a Laser Range

Finder (also known as a laser scanner) to monitor the activities in the bedroom environment. We employ totally eleven pressure sensor straps rather than a uniform pressure sensor array and categorize them into four groups, each being responsible for extracting features for one region of the bed top. Therefore, the pressure sensor readings of different sensor groups provides not only the sensor states covering different regions of the bed but also the positional information related to user's activity on the bed. In addition, the usage of the Laser Range Finder provides reliable information about people around the bed even under very low illumination. By fusing the two types of information appropriately, we can hereby infer one of the five situations {*Sleeping, Sitting, Caregiver Around, Leaving*, *Walking*} reliably. Experimental results have confirmed the effectiveness of our proposed system, which makes our system especially feasible for an elder staying in a bedroom environment. Our on-going work is to improve the recall rate by analyzing more detailed information based on readings of the eleven pressure straps and/or by rearranging the place of the laser scanner. In addition, human path tracking will be taken into account using the laser's detection technique.

Acknowledgments. This work was supported by National Science Council, National Taiwan University and Intel Corporation under Grant NSC99-2911-I-002-001.

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