Wearable Sensor-Based Behavioral Anomaly Detection in Smart Assisted Living Systems

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***Abstract*—Detecting behavioral anomalies in human daily life is important to developing smart assisted-living systems for elderly care. Based on data collected from wearable motion sensors and the associated locational context, this paper presents a coherent anomaly detection framework to effectively detect different behavioral anomalies in human daily life. Four types of anomalies, including spatial anomaly, timing anomaly, duration anomaly, and sequence anomaly, are detected using a probabilistic theoretical framework. This framework is based on complex activity recognition using dynamic Bayesian network modeling. The maximum-likelihood estimation algorithm and Laplace smoothing are used in learning the parameters in the anomaly detection model. We conducted experimental evaluation in a mock apartment environment, and the results verified the effectiveness of the proposed framework. We expect that this behavioral anomaly detection system can be integrated into future smart homes for elderly care.**

***Note to Practitioners*—This paper is motivated by the problem of developing a smart home environment that is able to understand the behavior of an elderly person living in it. The long term goal is to integrate intelligent home service robots into such smart homes for elderly care. Through the use of wearable motion sensors and the associated contextual information, we proposed and implemented a probabilistic framework for behavioral anomaly detection while avoiding the problems inherited in traditional vision-based anomaly detection approaches. The theoretical framework has been tested and evaluated in a simple laboratory environment as a proof of concept. Apparently, more realistic tests and thorough evaluation should be conducted for deployment in real home environments, which is the goal of our next stage of research. It is also desired to reduce the size and weight of the wearable motion sensors and improve their user-friendliness.**

***Index Terms*—Anomaly detection, assisted living, smart home, wearable computing.**

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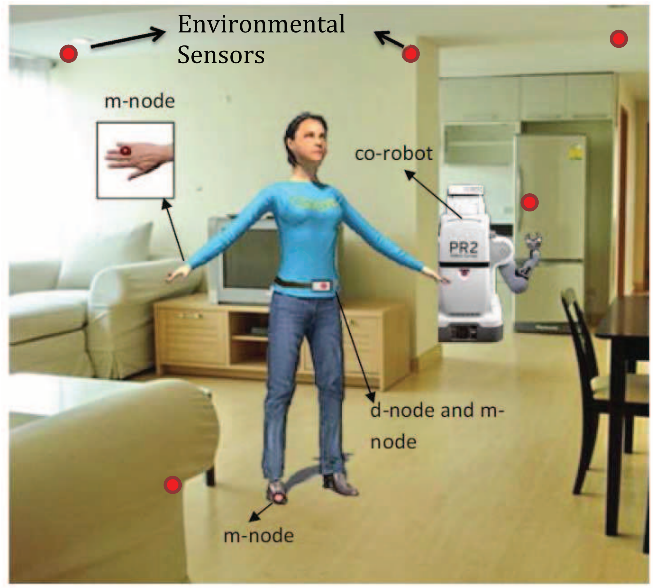


Fig. 1. Smart assisted living (SAIL) system.

I. Introduction

A. Motivation

THE world population is aging rapidly. The elderly population had increased to almost 810 million in 2012. In 2050, the number of aged people (60 and above) is predicted to reach a staggering 2 billion [1]. Elders have the option of going to adult day care, nursing homes, and hospice care. However many elders would prefer to stay in the comfort of their home, where they feel more confident. Helping them live a better life is very important and has great societal benefits. The best way to support them is to provide a physical environment that promotes the development and use of innovative technologies that encourage active and independent aging.

Toward this end, we are developing a *smart assisted living* (SAIL) system [2], [3] that can be used to provide support to elderly people in their own residence. The SAIL system, as illustrated in Fig. 1, consists of a body sensor network (BSN) [4], an environmental sensor network, and a companion robot, or co-robot. The body sensor network consists of a small set of wearable motion sensors (m-nodes) that collect body and limb motion and send them through wireless communication, such as Zigbee [5], to a wearable data processing node (d-node) that communicates with the companion robot. It is also possible that the wearable motion sensors can directly communicate with the companion robot without a d-node. The environmental sensor network consists of low-cost, simple passive infrared (PIR) sensors for human location tracking. From the data collected by these two sensor networks, the companion robot can infer human locations, activities, and intentions and respond correspondingly.

In such robot-assisted living systems, it is necessary to detect an elder's behavioral anomalies so that the robot may offer help when needed. In certain situations, behavioral anomalies can be life-threatening to the elders. For example, the elderly may fall down on the floor or lose consciousness on a sofa. This should be immediately intervened by the robot, or an alarm should be sent to the caregiver. Therefore, it is highly desirable to detect human behavioral anomalies in such assisted living systems. However, traditional approaches to behavioral anomaly detection usually rely on vision sensors on robots or environmental sensors. Vision-based solutions usually incur significant computational cost, while environmental sensor-based solutions have the disadvantage of high maintenance cost.

In this paper, we provide a new solution to this problem by developing a probabilistic theoretical framework to detect behavioral anomalies. Contrary to traditional approaches, we adopt wearable motion sensors as the main source of information, along with the contextual information from the sensors in the environment. This approach avoids difficulties faced by traditional vision-based anomaly detection approaches. The main advantages of using wearable sensors include the following:

1) the dimension of the motion data is significantly low compared with that of the visual data from cameras;
2) compared with visual sensors, wearable sensors minimize the privacy concerns, which are more acceptable to elderly people;
3) unlike visual sensors, wearable sensors are not influenced by environmental factors, such as lighting conditions.

Therefore, we believe that wearable sensors can provide an effective alternative to the visual sensors for daily activity recognition and behavioral anomaly detection. It is also worth noting that wearable sensors-based systems are more favorable economically due to the low cost and small number of wearable sensors needed. We implement and evaluate the algorithms in our SAIL testbed.

B. *Challenges and Objective*

Anomaly detection is an important research problem and has been studied in many application domains [6]. Anomalies are patterns in data that do not conform to well-defined normal patterns [6]. From the perspective of signal processing, anomalies can be generally categorized into two types: 1) point anomalies and 2) contextual anomalies.

If a data instance is considered different with respect to the rest instances, it is a point anomaly. Examples of point anomalies in daily behaviors include doing something at a unusual time or a wrong location. These anomalous patterns can be represented by a feature vector consisting of activity, time, and location. For example, lying unconsciously in the kitchen during the daytime is one example of these anomalies. Sleepwalking is also an example of doing something (walking) at a unusual time, although walking itself is normal if we do not consider the time.

A contextual anomaly is commonly found in time series data, which violates the sequential constraints and can be converted to point anomalies in the feature space. In human daily life, one example of contextual anomalies is a rare sequence of activities although each activity is normal when considering the time and location separately. For example, the sequence of $\{$preparing a meal $\rightarrow$ reading a book $\rightarrow$ having a nap$\}$ indicates that the subject may have forgotten to eat, which can be considered as a behavioral anomaly.

A straightforward approach to anomaly detection is to define regions representing normal patterns and find any features in the data that do not belong to the normal region. There are several factors that make this approach challenging. First, defining normal regions is difficult. Since normal patterns may cover a much larger domain compared with anomaly regions, defining normal regions and model normal patterns can directly affect the result of anomaly detection. In their daily life, people conduct all kinds of activities. The model of daily activity pattern may depend on the size of selected features from the sensing data. Therefore, defining normal regions can be task-specific. Second, establishing a clear boundary between normal and anomaly is challenging. In human daily life, different people have different living patterns, which makes this problem even worse. Third, it is difficult to obtain labeled data. Normal patterns usually account for a large share in the training data, which makes it difficult to capture and label anomalies. For daily behaviors, it is time-consuming to manually label data from long-term observation. Fourth, normal patterns may keep changing. In human daily life, people may change their patterns or schedules over time. Therefore, the model needs to adapt to the changing normal living patterns and also reduce the false positive rate when a normal pattern changes.

In this paper, we aim to develop a new theoretical framework to detect various behavioral anomalies in human daily life, while addressing the above-mentioned issues in anomaly detection. The remainder of the paper is organized as follows. Section II introduces the related work in behavioral anomaly detection. Section III describes the wearable sensor-based complex activity recognition algorithm. Section IV presents the anomaly detection approach, which mainly focuses on the modeling and learning for anomaly detection in human daily activities. Section V presents the detailed implementation of anomaly detection and the experimental results. Section VI concludes the paper and describes future work.

II. Related Work

There has been growing interest in detecting human abnormal daily behaviors in recent years. Here, we survey the existing work in this area. Based on the sensing modality, we can categorize the existing research in behavioral anomaly detection into three types:

1) vision-based approaches;
2) distributed sensor-based approaches;
3) wearable sensor-based approaches.

A. *Vision-Based Anomaly Detection*

Anomaly detection from visual data has received growing attention in recent years. With advanced image processing technologies, both human location and activity information can be extracted from visual data. In vision-based approaches, human moving trajectories are often used as key features to detect anomalous behaviors. For example, Gutchess *et al.* [7] built a prototype visual system to learn probabilistic models of activity and detect anomalies corresponding to unusual or suspicious behaviors using trajectories of moving vehicles or human subjects. Suzuki *et al.* [8] used a camera system to learn customer trajectory patterns in a store to detect anomaly behaviors for security purpose. They used a hidden Markov model (HMM) to represent the spatial–temporal patterns and estimate the likelihood for anomaly detection. Nayak *et al.* [9] localized and recognized events in a video involving multiple interacting objects and human subjects. They used HMM to detect normal events and treat the rest as anomaly. Emonet *et al.* [10] used probabilistic latent sequential motifs (PLSMs) [11] to extract an abnormality measure as the distance between normal instances and testing instances.

However, vision-based approaches have some disadvantages. Vision data are usually compromised by environmental factors, such as poor lighting conditions and occlusion. Vision-based activity recognition incurs a significant amount of computational cost. In addition, it may raise privacy concerns due to the use of cameras.

B. Distributed Sensor-Based Anomaly Detection

Activities of daily life can also be recognized using sensors distributed in an environment. For example, multiple radio frequency identification (RFID) sensors can be attached to different objects in a smart home. Activities related to objects can be inferred and sequences of using objects can be modeled to represent meaningful complex daily activities. Jakkula *et al.* [12] utilized the temporal nature of sensor data collected in a smart home to build a model of expected activities and to detect unexpected, and possibly health-critical events, in the home. In their work, activities are represented by temporal logic sequences of different objects. Shin *et al.* [13] developed a system using infrared (IR) motion sensors in a smart home to analyze human behaviors and assist the elderly in their independent living. The support vector data description (SVDD) method [14] was used to classify normal behavior patterns and detect abnormal behavioral patterns (point anomaly) based on the feature values of activity level, mobility level, and nonresponse interval. Suryadevara and Mukhopadhyay [15], [16] implemented a wireless-sensor-network-based home monitoring system that can determine the wellness of the elderly. They used distributed environmental sensors, such as pressure, contact, and electrical sensors, to monitor the use of the appliances. From the sensor data, certain predefined wellness functions can be calculated that can be used to detect whether abnormal behaviors occur. Recently, Riboni *et al.* [17] developed a novel method to recognize fine-grained abnormal behaviors of elderly people at home based on distributed sensor data, which can support the diagnosis of neurodegenerative diseases. They reported the preliminary results of implementation and testing in real home environments.

Overall, distributed sensor-based systems can provide useful information for human daily activity recognition. However, the cost for deploying such distributed sensors is high if the sensors are not cheap and the environment is large. Furthermore, such systems can only detect anomalies related to specific areas, and the types of recognized anomaly are limited.

C. Wearable Sensor-Based Anomaly Detection

Wearable motion sensors and physiological sensors can be used to monitor human activities and health conditions. However, the ambiguity due to the limited dimension of motion and physiological data brings difficulty. Teng *et al.* [18] used a wireless sensor to capture the motion data and then detected unconsciousness if there existed an extended period of motionlessness from the activity data. Yin *et al.* [19] used wireless sensors attached to a human body to detect abnormal activities, such as slipping on the ground, falling down backwards, and falling forwards. A one-class support vector machine (SVM) [20] is used to detect the point anomalies. Wood *et al.* [21] used wireless sensors worn by a resident to collect both motion and physiological data from which activity classification is implemented. The environment is also equipped with sensors to monitor environmental conditions, such as temperature, dust, motion, and light. This system is a combination of wearable sensors and distributed sensors in a smart home, which uses features from both types of sensors. Similarly Bang *et al.* [22] developed a real-time algorithm to recognize basic living activity in a home using a wearable motion sensor and smart home sensors. Only falling is detected in their system as anomalies.

In this paper, we also adopted a wearable sensor-based approach for behavioral anomaly detection. However, the difference between the work in our paper and that in existing literature is that we developed a general framework that covers four different types of anomalies (as detailed in Section IV) while the work in existing literature only deals with one or two types of anomalies.

In summary, the above three approaches to behavioral anomaly detection have both advantages and disadvantages. Multimodal sensors can be used to provide more information when designing an anomaly detection system. Existing approaches mostly focus on a single type of anomaly, while there are different types of anomaly in human daily behaviors. It is necessary to develop a new framework to cover multiple types of anomaly in a coherent way. This paper offers a solution toward this end, while using human motion data as the main data source.

III. Human Daily Activity Recognition

In this section, we describe the methodology for wearable-sensor-based activity recognition; based on that, we can develop behavioral anomaly detection in the next section. The body sensor network consists of three wearable motion sensors attached to the right thigh, the waist, and the right hand of the human subject, respectively. The reason for choosing these locations is that, through our experiment, we find that data collected from these locations can easily differentiate basic body activities, such as sitting, standing, and walking, while the hand gestures can be captured by the motion sensor on the hand. The motion sensor node we developed consists of a VN-100 orientation sensor module [23] from VectorNav Technologies, Dallas,

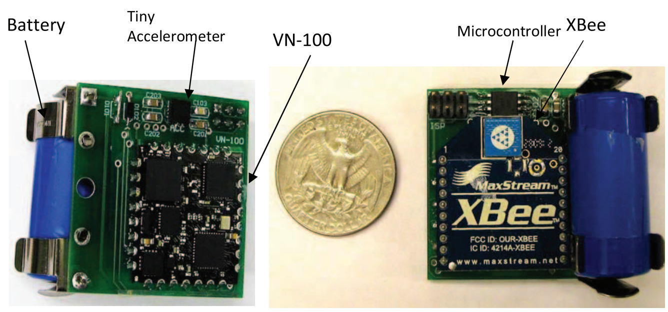


Fig. 2. Wearable motion sensor node [25].

TX, USA, for motion sensing; an XBee RF module for wireless communication; and a power management unit. The power is provided by a 3.3 v $2/3$ battery. The picture of the motion sensor node is shown in Fig. 2. The motion data include 3D orientation (roll, pitch, yaw), acceleration, angular rate, and magnetic field. The dimension of the sensor node is 36 mm $\times$ 35 mm $\times$ 18 mm, and the weight is about 40 g. With all the integrated circuits (ICs) in normal operation mode, the sensor node can operate continuously for about 5 h. With the implementation of an energy management system that takes advantage of the sleeping mode, the lifetime of the battery can be extended to about 14 h, which has been reported in our previous work [24]. In the current work, only 3D acceleration data is used for activity recognition.

Complex human daily activities involve simultaneous body activities and hand gestures in an indoor environment. Typical complex daily activities include "cooking in the kitchen," "eating dinner in the dinning room," and "using computers in the study room." The majority of human activity recognition research adopted computer vision-based approaches, which have the above-mentioned difficulties due to the use of cameras. We choose to use motion data from wearable motion sensors and location information to recognize complex daily activities.

We consider eight body activities: *sitting*, *standing*, *lying*, *walking*, *sit-to-stand*, *stand-to-sit*, *lie-to-sit*, and *sit-to-lie*, which are categorized into two types: stationary and motional activities. We consider five hand gestures: *using mouse*, *typing on a keyboard*, *flipping a page while reading a book*, *stir-fry cooking*, and *dining using a spoon*. Undefined gestures are categorized into the type of *other hand movements*. Although we only consider the above examples, more activities and hand gestures can be learned using a larger dynamic Bayesian network if needed.

In indoor environments, human daily activities (body activities and hand gestures) and locations are highly correlated [26]. For example, there are strong correlations between body activities and hand gestures during most daily activities, which can also be learned from training. Given a floor plan of an apartment, we can learn the probability distribution for each specific activity on the 2D map through training. To simplify the representation of the activity–location correlation, the given map of the mock apartment is segmented into different areas with corresponding probabilities of body activities and hand gestures. The location of the human subject is mapped into N_A semantic areas. Here, human location can be obtained through various ways, for example, using distributed sensors, such as PIR sensors or RFID. In our experiment, with the goal of verifying the overall theoretical framework, we assume the human location is provided by a Vicon motion capture system [27] available to us. In future work, we will replace the Vicon motion capture system with simple PIR motion sensors deployed in the environment.

In indoor environments, the transition of the location of a person usually follows certain patterns. For example, people walk from one area to another adjacent area, and there is a probability distribution according to the floor plan and personal preference. We assume the transition of locations is a discrete, first-order Markov process [28], which implies that the current location of the human subject is only related to his or her location at the previous time step. Meanwhile, there are constraints between two consecutive body activities and hand gestures as well. For example, if at one moment the person is sitting at the computer desk and typing on the keyboard, it is not likely that he or she will be walking in the following moment without standing up. In a similar way, we model the transition of body activity and hand gesture as a discrete, first-order Markov process.

To sum up, a person's location, body activity, and hand gesture have both intratemporal causal relationship and intertemporal constraints, which can be modeled using a three-level dynamic Bayesian network (DBN) model [29], shown in Fig. 3. A dynamic Bayesian network is a Bayesian network that has connected nodes in time domain and can represent temporal patterns. Human activities have strong temporal dependency, which allows them to be modeled by DBNs. The individual nodes in this graphical model represent hidden states, and the shaded nodes represent observations. The solid arcs correspond to causal dependencies between nodes in a one-time slice, while the dashed arcs correspond to the temporal dependencies between two-time slices t and $t+1$. The highest level of the model represents the person's location S^A, the middle level represents the person's body activity S^B, and the lowest level represents his or her hand gesture S^H. In the data preprocessing step, the observed measurements from the motion capture system are clustered into the observation O^A. The data from the motion sensors on the right thigh and the waist are combined and clustered into the observation O^B. The right-hand sensor measurements are clustered into the observation O^H.

Based on this DBN model, given the sequence of observations in terms of O^A, O^B, and O^H, we can infer the hidden states, i.e., S^A, S^B, and S^H through Bayesian filtering. The average accuracy of the activity recognition algorithm is above 80% [25]. A more detailed discussion of the complex activity recognition can be found in our previous work [25], [30].

IV. Behavioral Anomaly Detection

There are different types of anomaly in human daily life, such as falling down on the floor, forgetting to take medicine, working overtime, and sleepwalking. We need a coherent model to integrate different types of anomalies. The proposed anomaly detection model is built based on the DBN model described in the previous section. We enhanced the DBN with new nodes related to time, which enables the detection of time-dependent behavioral anomalies. In the following sections, we will first

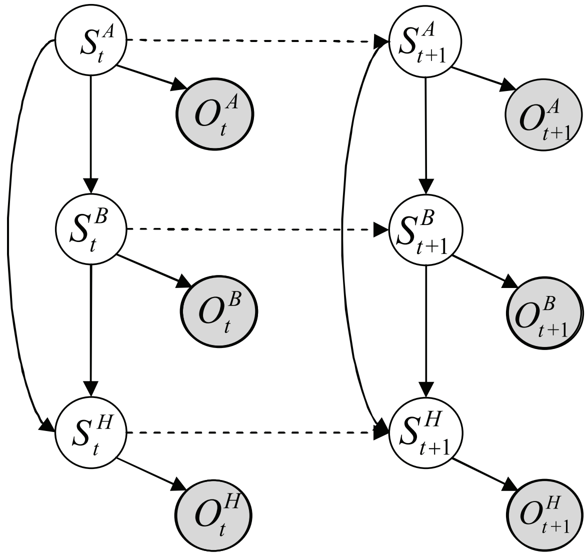


Fig. 3. Two-slice dynamic Bayesian network of the activity and gesture model, showing dependencies between the observed and hidden variables. Observed variables are shaded. Intratemporal causal links are solid; intertemporal links are dashed.

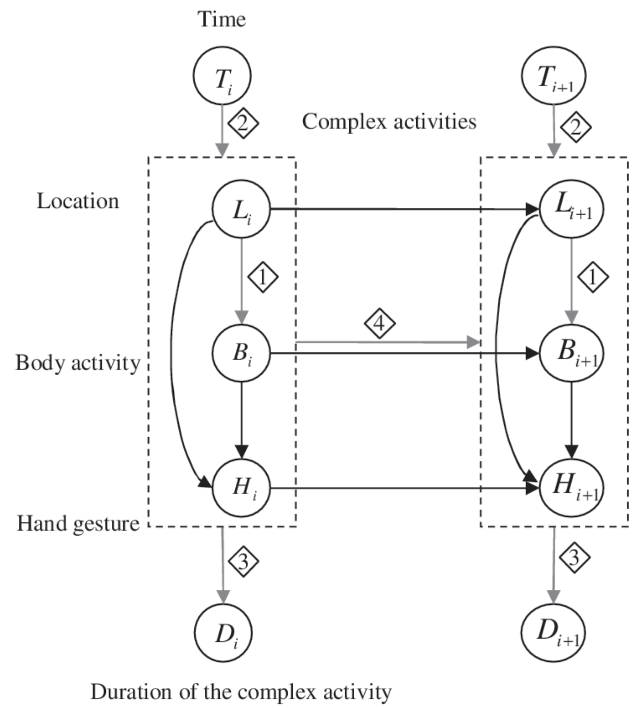


Fig. 4. Anomaly detection model considering four types of anomaly: 1) spatial anomaly; 2) timing anomaly; 3) duration anomaly; and 4) sequence anomaly.

describe the anomaly detection model, and then we will explain the learning of the model.

A. Anomaly Detection Model

Based on the above DBN model for complex activity recognition, we can develop the anomaly detection model. We consider the following four types of anomaly in complex daily activities. Here Type 1, 2, and 3 are point anomalies, while Type 4 is a contextual anomaly:

- *Type 1—Spatial anomaly:* indicates that the human subject is doing something at a wrong place, such as lying on the floor in the kitchen or bathroom;
- *Type 2—Timing anomaly:* indicates activities at an unusual time, such as sleepwalking at midnight;
- *Type 3—Duration anomaly:* may indicate unhealthy living patterns. For example, the user works on the computer for a very long time without a break;
- *Type 4—Sequence anomaly:* indicates a low transition probability between two consecutive complex activities. For example, after cooking, the user forgets to eat and starts working by the computer immediately.

In order to detect multiple types of anomaly in a coherent framework, we propose an anomaly detection model that includes the time, activity, duration, location, and activity transitions, as shown in Fig. 4. Compared with the activity recognition model in Fig. 3, the time instances with the same complex activity state are combined, and multiple states in the activity recognition model are converted into one state. Therefore, it can be considered an event-based anomaly detection model. Accordingly, the subscript of each state changes from t to i. The anomaly detection model consists of the complex activity node and two new nodes: time T_i and duration D_i. Since we already considered the location transition constraints in the complex activity recognition model, in the anomaly detection model, these constraints are not used. The four types of anomaly, marked with numbers 1 through 4, can be described using the constraints between each node in Fig. 4. Each edge represents a probability distribution between the two states that are used to detect anomalies.

In the anomaly detection model, we can derive four types of probabilities as follows.

1) The spatial anomaly is represented by a low probability of body activity given the location information $P(B_i|L_i)$. Since spatial anomalies are represented by activities occurring at wrong locations, we use the location and body activity tuple to estimate $P(B_i|L_i)$.
2) The timing anomaly is represented by a low probability of the time given the complex daily activity $P(T_i|C_i)$. Current time is a node of anomaly detection model. As time is utilized as direct constraints on the activities, the probability of activities given the current time can be learned using historical data.
3) The duration anomaly is represented by a low probability of the duration given the current complex activity $P(D_i|C_i)$. Activities are first detected without time. Then, the duration is accumulated if the activity is continuously detected. The tuple of a complex activity and its accumulated duration from its beginning is used to represent the period of time that the activity has lasted.
4) The sequence anomaly is represented by a low probability of complex activity given the previous complex activity $P(C_{i+1}|C_i)$. The transition probability between different complex activities can be used to detect abnormal sequences of activities. In the fields of computational linguistics and probability, n-gram [31] is used to represent

a contiguous sequence of n items from a given sequence of text or speech. Since the sequential constraints in a sequence of activities can be modeled similarly to the grammar in a language, n-gram can be used as sequential features. Models built from n-grams are $(n-1)$-order Markov models. In the anomaly detection model, n-gram can be used to describe a sequence of different complex activities. For example, when $n = 3$, an n-gram can be {cooking $\rightarrow$ reading a book $\rightarrow$ using the computer}. In this sequence, although each individual activity does not indicate anomaly, it is obvious that the human subject did not eat after cooking. Therefore, *forgetting to eat* can be detected using n-gram features.

B. Learning of Anomaly Detection Model

In order to learn the anomaly detection model, semi-supervised learning [32] is used. Semi-supervised learning methods use unlabeled data to modify hypotheses obtained from labeled data alone. In semi-supervised learning, large amounts of unlabeled data, together with the labeled data, are used to build better classifiers. Because semi-supervised learning requires less human effort and gives higher accuracy [32], [33], it is of great interest both in theory and in practice. In the training process of our anomaly detection model, it is assumed that the training data have labeled instances for the normal class only. The four types of probabilities are learned from normal activities and living patterns. We recorded normal living activity data in our laboratory environment and estimated the corresponding probabilities from the labeled video stream. Maximum-likelihood [34] and Laplace smoothing [34] techniques are used to learn the probabilities in the anomaly detection model. Using the unlabeled testing data, the four probabilities are compared with a benchmark threshold. When the detected probability is lower than that threshold, a decision can be sent to indicate an anomaly has been detected.

The results of tests using different thresholds are compared using the $F1$ score [35] and the receiver operating characteristic (ROC) curve [36] so that the best threshold can be determined for better performance of anomaly detection.

Maximum-Likelihood Estimation: Maximum-likelihood estimation is used to calculate the parameters of the anomaly detection model. For the four types of anomaly—spatial anomaly, timing anomaly, duration anomaly, and sequence anomaly—there are four probability models to learn, which are $P(B_i|L_i), P(T_i|C_i), P(D_i|C_i)$, and $P(C_{i+1}|C_i)$ (bigram probability), as described in the previous section. Here, we take $P(B_i|L_i)$ of spatial anomaly as an example to explain the method. Let

$$\theta_{jk} := P(B_i = b_j|L_i = l_k) \tag{1}$$

where b_j is one of the possible value of body activities and l_k is one possible value of locations. Given the property of conditional probabilities, we have

$$\sum_j \theta_{jk} = 1. \tag{2}$$

In addition, we need to estimate the parameters that define the prior probability over L_i as

$$\pi_k := P(L_i = l_k). \tag{3}$$

We can estimate these parameters using maximum-likelihood estimation, which calculates the relative frequencies of the different events in the data.

Maximum-likelihood estimation for θ_{jk}, given a set of training samples D, is given by

$$\hat{\theta}_{jk} = \hat{P}(B_i = b_j|L_i = l_k) = \frac{\#D\{B_i = b_j \wedge L_i = l_k\}}{\#D\{L_i = l_k\}} \tag{4}$$

where the $\#D\{x\}$ operator gives the number of elements in the set D that satisfy property x.

One shortcoming of this maximum-likelihood estimation is that it can sometimes result in θ estimates of zero, if you have not seen the data in the training samples satisfying the condition in the numerator. Therefore, it is necessary to use a smoothed estimate, which brings in a small number of uniformly distributed dummy examples.

Laplace Smoothing: Laplace smoothing is often used to avoid zero probability in the training process, which is due to unseen events. The smoothed estimate is given by

$$\hat{\theta}_{jk} = \hat{P}(B_i = b_j|L_i = l_k) = \frac{\#D\{B_i = b_j \wedge L_i = l_k\} + p}{\#D\{L_i = l_k\} + pN_B} \tag{5}$$

where N_B is the number of distinct values B_i can take, and p determines the strength of this smoothing. If p is set to 1, this approach is called *add-one smoothing*, also called *Laplace smoothing* [37]. Laplace smoothing assumes that every seen or unseen event occurred one more time than it did in the training data.

Real-Time Learning: After all the parameters have been learned from the historical data using maximum-likelihood estimation and Laplace smoothing, the model can be used for anomaly detection. During the online anomaly detection process, a user interface is used to identify false detection when the human subject thinks that it should be normal. When an anomaly is detected, the system can show a confirmation dialog on a mobile device such as a smart phone carried by the human subject. If it is found to be a normal activity, the corresponding probability can be updated using the new instance. Otherwise, it is considered as a true anomaly.

The probability matrix P can be updated as follows:

$$P' = \frac{P \cdot (\text{Length} - 1) + \{FP\}}{\text{Length}} \tag{6}$$

where P' is the updated probability matrix, $\{FP\}$ is a matrix with 1 at the position of the falsely detected abnormal activity and 0 for all other positions. Length is the size of the event window used for model updating. A small length indicates that the model can be changed easily when there is a rare activity, which also means the model can adapt to new daily behaviors quickly. While a large length can make the model more stable, it takes a longer time to learn changed probabilities. Therefore, the parameter length needs to be adjusted in practice to control the sensitivity and robustness.

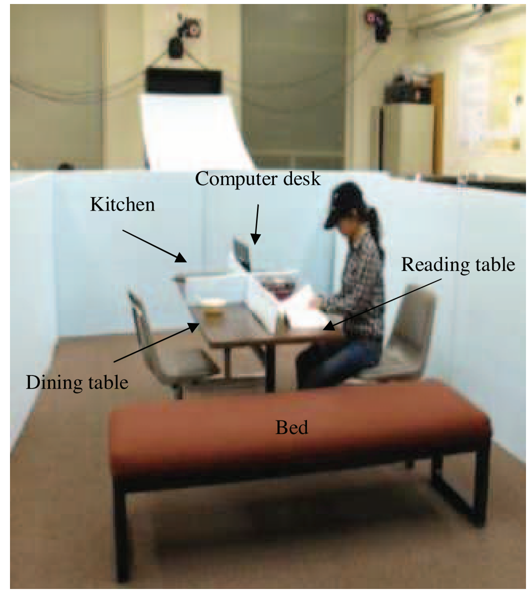
V. Experiments and Results

A. Experiment Design

In this section, we describe the detailed implementation of the proposed probabilistic framework for anomaly detection. A mock apartment is set up, which is shown in Fig. 5. There are six areas: computer desk, reading table, kitchen, dining table, bed, and free space. The human subject wears three wireless sensors on the right thigh, the waist, and the right hand, respectively. The human subject performs daily activities following a normal schedule, while abnormal activities are performed randomly. The Vicon system, installed on the wall is used to capture the location of the human subject, and a video camera is used to obtain the ground truth of human activities. The frame rate of the motion capture system is 100 Hz, and the error of location tracking is 0.7 mm. In our future work, we will replace the Vicon system with a set of PIR motion sensors, which can achieve a location tracking error of about 25 cm, which is sufficiently accurate.

A PC is used to collect data and run both activity recognition and anomaly detection in real time. The program consists of two threads: a data sampling thread and a data processing thread. First, the sampling thread collects data from three wireless motion sensors and the synchronized location information from the Vicon system. The body sensor network consists of three motion sensors and a Zigbee wireless receiver. Each data packet has a time stamp; thus data from these motion sensors are synchronized. The location data are streamed via the WiFi network and sampled at a rate of 1 Hz. Second, the processing thread deals with the sampled data in three steps: preprocessing, activity recognition, and anomaly detection. The recognition model generates a vector representing the body activity and hand gesture, which is used as part of the input for the anomaly detection model. In the anomaly detection module, four types of anomaly probabilities (spatial anomaly, timing anomaly, duration anomaly, and sequence anomaly) are estimated and compared with the corresponding threshold, which will trigger the alarm if it is below that threshold. In the training phase, the human subject performs normal daily activities in the mock apartment, and the data are collected from which the probabilities can be learned.

Due to the limited space of the mock apartment and the limited experiment time, we have the following assumptions. First, the Gaussian distribution is used to model the duration probability. In order to process the discrete time duration values, we use 24 bins to sample the Gaussian distribution. For duration anomaly, we only consider activities that exceed the normal duration limits. Therefore, we ignore the low probability for small duration values in the distribution and replace it with the probability at $(\bar{D} - 3\sigma)$, where $\bar{D}$ and σ are the mean and standard deviation of the duration. Second, with the goal of verifying the theoretical framework, we modify the model to scale down the time in the experiment. We use 24 min to represent 24 h, whereas



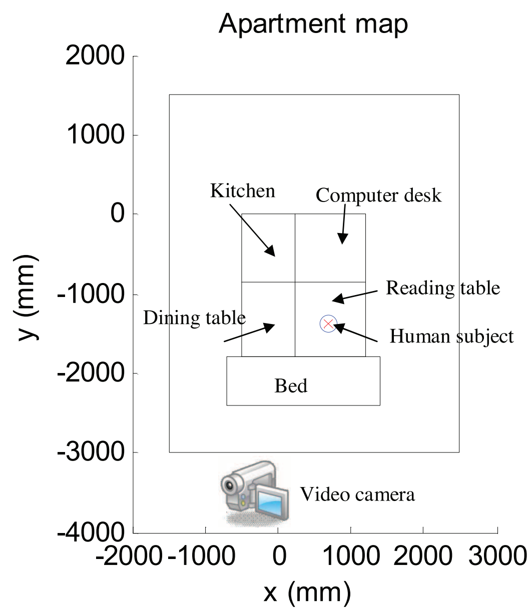


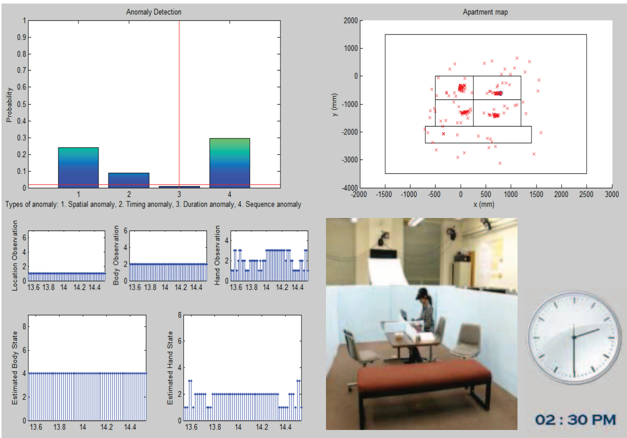
Fig. 5. Mock apartment and its layout used in the experiment.

the corresponding parameters for timing anomalies and duration anomalies are adjusted to match the new time scale.

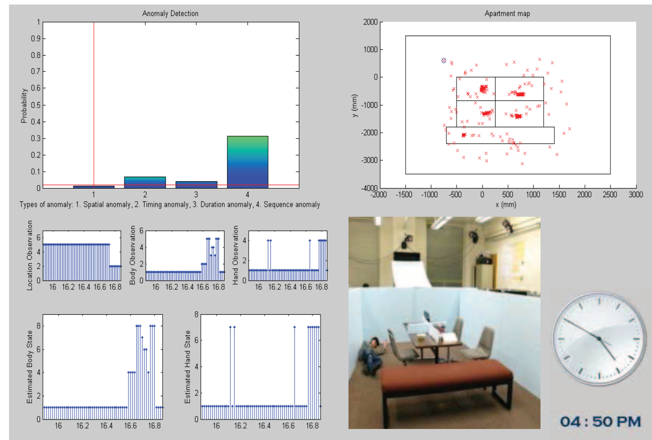
We first used simulated activity sequences to validate the anomaly detection model. Then experiments are conducted in the mock apartment to test the performance of anomaly detection. Within the 24-min period, the human subject follows a script of a daily schedule, as shown in Table I. Different types of anomaly are generated and inserted into the normal daily schedule.

B. Experimental Results

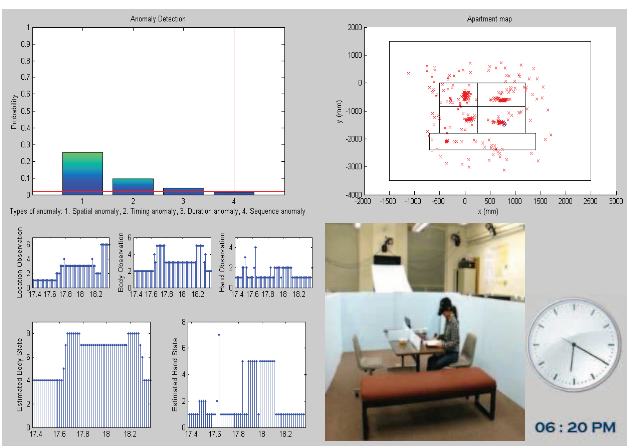
In this section, we present the experimental results. On the server PC, screen capture software is used to record the output of the anomaly detection results. The captured results can be compared with the ground truth recorded from a regular video recorder. The recorded video of the experiment is synchronized with the output of the activity recognition. Some significant



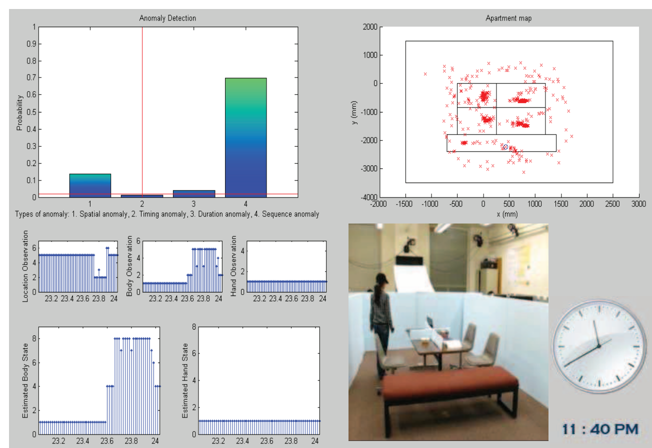
(a)



(b)



(c)



(d)

Fig. 6. Results of anomaly detection. The top left plot of each subfigure shows the probability of spatial activity, timing, duration, and sequential activities. The plots in the lower left areas are O^A, O^B, O^H, and results of S^B, S^H, respectively. The top right plot is the location of the subject. The picture in the lower right is the snapshot from the video camera. Labels for activity result: 1) lying; 2) lie-to-sit; 3) sit-to-lie; 4) sitting; 5) sit-to-stand; 6) stand-to-sit; 7) standing; and 8) walking. Labels for gesture result: 1) nongesture; 2) using a mouse; 3) typing on a keyboard; 4) flipping a page; 5) stir-frying; 6) eating; and 7) other hand movements.

TABLE I
EXAMPLE OF NORMAL SCHEDULE OF THE HUMAN SUBJECT

Time	Standard deviation	Activities
6:00 - 7:00 am	±1 hour	Wake up in the morning
7:00 - 7:30 am	± 15 minutes	Prepare breakfast and have breakfast
8:00 - 11:00 am	± 30 minutes	Read or work on computer
11:00 - 12:00 pm	± 15 minutes	Prepare lunch and have lunch
1:00 - 5:00 pm	± 30 minutes	Nap or read or work on computer
5:00 – 5:30 pm	± 15 minutes	Prepare dinner and have dinner
6:00 - 9:30 pm	± 30 minutes	Read or work on computer
9:30 - 10:00 pm	± 30 minutes	Go to bed

frames are shown in Fig. 6. The top left plot of each subfigure shows the probability of spatial activities, timing, duration, and sequential activities patterns, and the low values indicate the corresponding anomalies. In Fig. 6(a), the subject works on the computer for over 2 h, which triggers the duration anomaly alarm at 2:30 p.m. In Fig. 6(b), she falls down to the floor at 4:50 P.M., which triggers the spatial anomaly alarm, and the probability of timing and duration are also low at the meanwhile. In Fig. 6(c), she goes to read directly after cooking and triggers the sequence anomaly alarm at 6:20 P.M., which indicates that she may have forgotten to eat. In Fig. 6(d), she gets up and walks around after 2 h of sleep at 11:40 P.M.. The timing anomaly is triggered, which indicates she is sleepwalking.

To evaluate the performance of anomaly detection, the video camera recorded the ground truth. The activity instance in the testing sets was manually labeled as normal if it follows the schedule and abnormal otherwise. The threshold in anomaly detection is modified to compare the performance of the model. Statistical tools such as the confusion matrix are adopted to evaluate the performance of anomaly detection. Based on the confusion matrix, it is straightforward to derive the following terms:

TABLE II
EXPERIMENTAL METRICS (NUMBER OF ACTUAL ANOMALIES: 69 AND NUMBER OF NORMAL INSTANCES: 3800)

Threshold	0.001	0.005	0.01	0.02	0.025	0.03	0.035	0.04
Anomaly detected	41	50	57	69	76	76	124	721
False positive	0	0	0	0	7	7	55	652
True positive	41	50	57	69	69	69	69	69
Recall	0.5942	0.7246	0.8261	0.9710	1.0000	1.0000	1.0000	1.0000
Precision	1.0000	1.0000	1.0000	1.0000	0.9079	0.9079	0.5565	0.0957
$F1$ score	0.7455	0.8403	0.9048	0.9853	0.9517	0.9517	0.7151	0.1747

recall [sensitivity or true positive rate (TPR)]; precision [positive predictive value (PPV)]; false positive rate (FPR); and accuracy. The traditional F-measure or balanced F-score (F_1 score) is the harmonic mean of precision and recall:

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}. \quad (7)$$

For anomaly detection, the data are skewed, most of which are in the normal class. When 1% of the data are anomalies, a trivial classifier that outputs normal for every data instance will have the accuracy of 99%. Therefore, the accuracy may not be able to evaluate the performance. The F_1 score considers both the precision and the recall of the test to compute the score. It can be interpreted as a weighted average of the precision and recall, where an F_1 score reaches its best value of 1 and worst score of 0.

We conducted various experiments and collected the results. The related statistics, including recall, precision, and F_1 score, are listed in Table II, which is calculated based on 3800 normal instances and 69 actual anomalies.

VI. CONCLUSION

In this paper, motivated by the goal of providing a more intelligent living environment for the elderly, we propose an approach to detecting anomalies in human daily activities using wearable sensors. The proposed probabilistic framework allows coherent detection of four different types of daily activity anomalies, such as falling to the ground, not following the normal schedule, working overtime, and sleepwalking. The time and different activity instances are used to model the normal living patterns. Maximum-likelihood estimation and Laplace smoothing are used in the semi-supervised learning. The model can be updated online using user confirmation in order to adapt to changed probabilities and living patterns over time. Experiments in a mock apartment environment verified the proposed framework, and the real-time results show the effectiveness of the anomaly detection system. In the future, we will test this wearable sensor-based behavioral monitoring system on more human subjects in more realistic environments. We expect that future smart homes can be made truly smart so that they can better serve the people living in them.

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