Context-Aware Fall Detection Using A Bayesian Network

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ABSTRACT
Human activity recognition is regarded as one of the most important topics in ubiquitous computing. In this paper, we focus on recognizing falls. Falls are a leading cause of death among elderly people. Most existing fall detection techniques focus on studying isolated fall motion under restricted, clearly defined conditions, and thus suffer from a relatively high false positive rate induced by many other activities that resemble a fall. In this paper, we present an integrated fall detection framework that incorporates isolated fall detection algorithms with context information using a Bayesian network. The context information can include a person's age, personal health history, physiological measurements (such as respiration, blood pressure, heart rate, etc.), physical activity level and location. These additional sources of information are complement inputs to our framework to improve decision accuracy in recognizing activities such as a fall. A Bayesian network is constructed to structure the probabilistic dependencies between isolated fall detection result and various contextual sensor readings, and perform inference on the likelihood of a fall in a given context. Preliminary experimental results demonstrate that context information can play a significant role in improving fall detection accuracy and reducing both false negative and false positive rates. We also demonstrate that our probabilistic Bayesian model can produce informative inference results even when partial contextual information is observed.

Author Keywords
Fall Detection, Context-Awareness, Bayesian Network, Wireless Body Area Sensor Network, Ubiquitous Healthcare

ACM Classification Keywords
I.2.1 Artificial Intelligence: Applications and Expert Systems; I.5.4 Pattern Recognition: Applications

General Terms
Design, Experimentation, Performance

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INTRODUCTION
Falls and fall-induced injuries are a leading cause of death among elderly people. Based on the survey in [1], more than a third of people aged over 65 in America fall at least once every year. Among these falls, 10% to 15% cause serious injuries. Therefore, real-time and reliable fall detection is key to reducing these injuries and saving people's lives.

With low-cost, miniatured MEMS sensors worn on the human body, it is feasible to monitor mechanical parameters of the human body such as dynamic accelerations, angular velocity, torso tilts, and body postures to detect falls. Compared to typical activities such as walking, running, and riding a bicycle, a fall is non-periodic, with a much shorter duration and a large intra-class variance. Furthermore, some activities, such as jumping, lying down on the bed, and standing up from a sitting position, share a very similar mechanical realization with falls where even state-of-the-art learning machines may still fail and give the wrong classification results. Therefore, a fall is regarded as a very difficult activity class to be detected and recognized.

Existing fall detection techniques can be classified into three categories. One technique takes mechanical parameter measurements and segments them into several stages with one or more pre-defined thresholds for each stage. A fall is detected if and only if all the thresholds are exceeded in a given sequence [2]. Time series analysis is a second technique, in which a fall is detected if the overall shape of the mechanical parameter signal is matched with a static pre-defined signal for fall [3]. The third technique models the fall motion as a dynamic statistical model such as Hidden Markov Model that incorporates the temporal aspects of the fall motion in the recognition process [4]. However, these techniques all focus on studying isolated fall motions under various restricted conditions. Although they can achieve near perfect true positive detection rates, they still suffer from relatively high false positive rates induced by many fall-like activities.

To improve the reliability of the fall detection system with a special focus on reducing the false positive rate, in this work, we utilize context information, such as a person's physical activity status, current physiological conditions, his/her personal health records, and the location information. These context information normally has a strong semantic meaning and can provide important "hints" that help to differentiate falls from fall-like activities. For example, a person with a Parkinson's disease (PD) walking on the street is more likely to fall than a healthy man sitting on the sofa at home.

However, in a real-world deployment, since resources are always limited, it is impossible to collect and take all kinds of context information into consideration. Therefore, a probabilistic framework is needed such that less important context information can be ignored in a probabilistic manner. Another benefit of adopting a probabilistic framework is that it provides the capability of handling partial corruption of the input data. This is especially true in our scenario where context information is sensed and gathered from various contextual sensors. Real world sensors do not always operate as they should due to a series of issues such as noise, hardware failure, and power limitations. Therefore, by building our context-aware fall detection system on top of a probabilistic framework, it is capable of reasoning with incomplete and noisy input observations.

In this paper, we propose an integrated probabilistic fall detection framework that combines an isolated fall detection algorithm with context information. Figure 1 illustrates the main idea of the framework. Specifically, we structure the probabilistic dependences between the isolated fall detection algorithm and various contextual sensor readings as a Bayesian network. The Bayesian network acts as a customized personal knowledge base and performs inference to calculate the likelihood of a fall in the given context. By performing probabilistic inferences, we provide the inquirer with more useful information than only one answer whose certainty is unknown. As a consequence, the inference result can be used for both fall risk analysis and fall prevention.

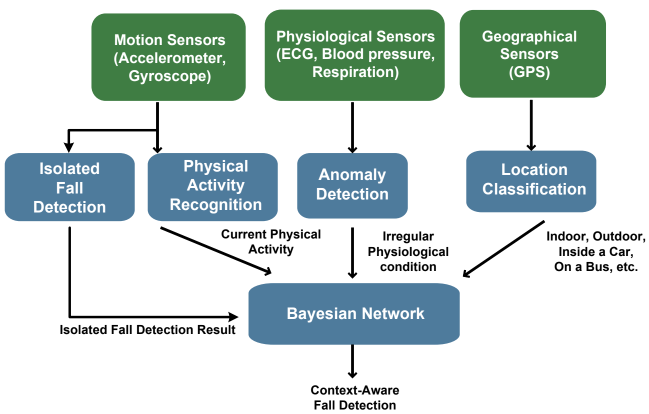


Figure 1. Context-aware fall detection framework

The paper is organized as follows. We first introduce the context information incorporated in our framework. Then we present the Bayesian network model for context-aware fall detection. Next, we describe the sensing platform used in this work. Model evaluation and preliminary experimental results are then presented and discussed. Finally, we conclude this work and give directions for future work.

CONTEXT INFORMATION

Context is defined as any information that can be used to characterize the circumstance in which an event occurs [5]. This concept has been extensively employed and played a significant role in many pattern recognition problems. Examples include computer vision, human speech recognition, and natural language processing. In the domain of ubiquitous healthcare, context awareness is mainly concerned with the recognition and interpretation of a person's physical activities and physiological conditions [6]. In our framework, we utilize four types of context information: (1) physical activity; (2) physiological condition; (3) personal health record; and (4) location. Based on the common senses and the related medical research results (which will be presented later in this section), we believe that these are the four most important context sources that could help to detect falls.

Physical Activity: A subject's physical activity status plays an important role in his/her context interpretation, and therefore can be used to detect falls. For example, although people may fall under different conditions for different reasons, based on the study performed in [7], there is a higher probability of falling when people are walking or going up/down stairs. For elderly people, according to [8], they are more likely to fall when they just get out of bed after a sleep due to the temporary muscle weakness and the balance disorders. In addition, 14% of subjects who fell reported lying on the ground, unable to get up for five minutes or more [7]. This finding indicates that the temporary activity limitation is also a good indicator of a fall.

Physiological Condition: Many medical research results relate falls to a subject's physiological condition. Heartbeat rate and blood pressure are the two most important physiological signals that are strongly associated with falls. According to [9], cardiac arrhythmia accounts for about 10% of falls due to fainting. For blood pressure, a large drop in blood pressure (20 mmHg) is an attributable diagnosis in 47% of subjects with previously unexplained falls. Therefore, a subject's current physiological condition could serve as important context information to detect falls.

Personal Health Record: Certain illnesses and injuries are shown to have very strong associations with falls. For example, according to [10], the carotid sinus syndrome disease, one of whose symptoms is a reduction of blood pressure exceeding 50 mmHg, is diagnosed to be a cause of syncope and fall for the elderly people. Moreover, based on the research results presented in [11], people with a history of stroke, Parkinson's disease (PD), diabetes, arthritis of the knees, impairment of gait, and previous falls experience are more likely to fall than people who do not have those illnesses.

Location Information: According to [7], 52% nonsyncopal falls occurred in or around the subject's residence. For people aged 80 and older, 61% of falls happened at home. These results indicate that location data could also provide useful information to help detect falls.

BAYESIAN NETWORK

In this section, we first give a brief introduction of the Bayesian network. Then we describe our Bayesian network model for context-aware fall detection.

Introduction to Bayesian Network

A Bayesian network is a probabilistic graphical model that represents a set of random variables and their joint probability distribution via a directed acyclic graph (DAG) [12]. Each node in the network represents a random variable. If there is an directed link from node x to node y, x is said to be a parent of y, which indicates that x has a direct influence on y. The absence of a link between two nodes encodes either an absolute independence or conditional independence given their parent nodes. To make a Bayesian network a complete description of the domain, besides the network structure, both the prior and conditional probability distributions of each node given its parents need to be specified. These information is normally organized in conditional probability tables (CPTs). By leveraging the conditional independences encoded in the network structure, the joint probability distribution of the variables the Bayesian network incorporates can be factored and is given by

$$P(\boldsymbol{x}) = \prod_{i=1}^{n} P(x_i|\boldsymbol{Pa}_i) \tag{1}$$

where $\boldsymbol{x} = \{x_1, \dots, x_n\}$ represents the variable set, and $\boldsymbol{Pa}_i$ denotes the parents of node x_i [13].

Our Solution

In our scenario, we structure the conditional dependencies between the isolated fall detection algorithm, the context information introduced in Section , and our query of interest (whether the subject falls) as a Bayesian network illustrated in Figure 2. As our first step to approach this problem, the structure of our Bayesian network is constructed manually based on basic causal and domain knowledge. To answer the query, exact inference is performed to compute the posterior probability of the query variable given available contextual observations. In the remainder of this section, we start with the formal definition of the variables we incorporate in the model. Then we explain how we derive the prior and conditional probabilities that relate the variables to one another. At last, the inference algorithm is covered.

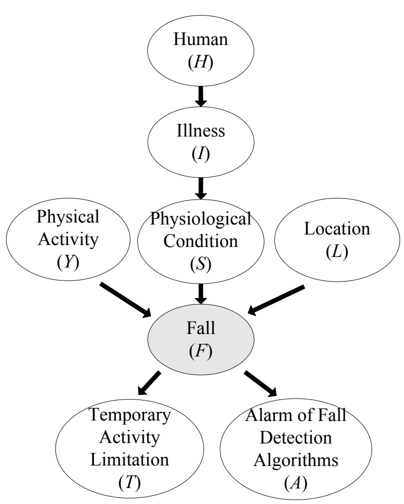


Figure 2. The Bayesian network model for context-aware fall detection

Random Variables

As illustrated in Figure 2, eight variables {human, illness, physiological condition, physical activity, location, fall, temporary activity limitation, alarm of isolated fall detection algorithm} are incorporated in our model.

Variable 1: Human

Let H denote the *Human* variable. In our model, we categorize subjects (*Human*) based on their ages and use age values to represent subjects. We use age values because many fall-related medical conditions, such as stroke and Parkinson's disease have strong associations with subjects' ages.

Variable 2: Illness

Let I denote the *Illness* variable. This variable represents the subject's personal health record, which records the subject's illnesses (e.g. cardiac problem, obesity), injuries (e.g. lame leg), and previous experiences (e.g. previous fall history) that have strong associations with falls.

Variable 3: Physiological Condition

Let S denote the *Physiological Condition* variable. This variable represents whether the subject's is suffering from an irregular physiological condition which are highly related to falls, Examples are cardiac arrhythmia and a large drop in blood pressure. In our model, the probability of the occurrence of an irregular physiological condition is modeled to be totally dependent on the subject's personal health record. In addition, the irregular physiological condition is modeled to be one of the three direct causes of a fall (Other two are *Physical Activity* and *Location*).

Variable 4: Physical Activity

Let Y denote the *Physical Activity* variable. This variable represents the subject's current physical activity status, which includes activities of daily living such as walking, sitting, and sleeping. It also contains fall-prone activities such as getting up from bed and going up/down stairs.

Variable 5: Location

Let L denote the *Location* variable. This variable represents the subject's location information indicating whether the subject being monitored is at home, in a car, or outdoors.

Variable 6: Fall

Let F denote the *Fall* variable. This variable represents whether the subject falls or not. Our objective is to determine its posterior probability given other observed variables.

Variable 7: Temporary Activity Limitation

Let T denote the *Temporary Activity Limitation* variable. As explained in Section 2, many people who fell reported lying on the ground and were unable to get up for five minutes or more. Therefore, in our Bayesian model, we model this information as a consequence of fall.

Variable 8: Alarm of Fall Detection Algorithm

Let A denote the *Alarm of Fall Detection Algorithm* variable. This variable represents the recognition result of the

(a) MotionNode platform

(b) During data collection, MotionNode is packed firmly into a mobile phone pouch and attached to the subject's front right hip

Figure 3. The sensing platform and its placement during experiments

isolated fall detection algorithm. We model this information as a consequence of fall as well.

It should be note that our Bayesian model does not include variables corresponding to factors such as environmental hazards (such as slippery surfaces) that may be potential reasons for falls. These factors (or a potentially infinite set of circumstances) are actually summarized in the uncertainty associated with the links directed to the fall variable. In this way, less important contextual information is filtered out.

Prior and Conditional Probabilities

To customize the model for each individual subject, both prior and conditional probabilities should be learned from the subject's past experience and personal health record. Once the prior and conditional probability tables are constructed, probabilistic inferences can be performed.

Variable Elimination for Exact Inference

Inference in Bayesian network refers to the process of computing posterior probabilities of unobserved variables given the values of observed variables. Existing inference algorithms can be classified into two categories: exact inference, and approximate inference. Approximate inference approach is normally employed when running exact inference is computationally expensive or the problem itself is computationally intractable. In our problem, since our model only incorporates discrete variables, it is feasible and preferable to use the exact inference approaches [14]. In this work, we use variable elimination exact inference algorithm to calculate the posterior probabilities. Compared to other exact inference algorithms such as clique tree, variable elimination is fast and memory efficient when only a limited number of inferences are performed. As a consequence, variable elimination is preferred when inference results need to be generated in real time. This is exactly the case for fall detection. Variable elimination achieves fast inference by exploring the structure of the Bayesian network and marginalizing the non-observed non-query variables one by one by distributing the sum over the product [13]. For example, in our model, if we denote the variables in Figure 2 by their initial letters, the likelihood of fall when the alarm of the isolated fall detection algorithm fires, that is, $P(F|A)$, can be calculated efficiently using variable elimination as

$$\begin{aligned} P(F|A) &= \alpha \cdot \sum_{H,I,S,L,Y,T} P(F,H,I,S,L,Y,T,A) \\ &= \alpha \cdot \sum_{H,I,S,L,Y,T} P(H)\cdot P(I|H)\cdot P(Y)\cdot P(S|I) \\ &\cdot P(L)\cdot P(F|Y,S,L)\cdot P(T|F)\cdot P(A|F) \\ &= \alpha \cdot P(A|F)\cdot \sum_{T} P(T|F)\cdot \sum_{L} P(L)\cdot \sum_{Y} P(Y) \\ &\cdot \sum_{S} P(F|Y,S,L)\cdot \sum_{I} P(S|I)\cdot \sum_{H} P(H)\cdot P(I|H) \end{aligned} \tag{2}$$

where α is the normalization factor such that the value of $P(F|A)$ is between 0 and 1.

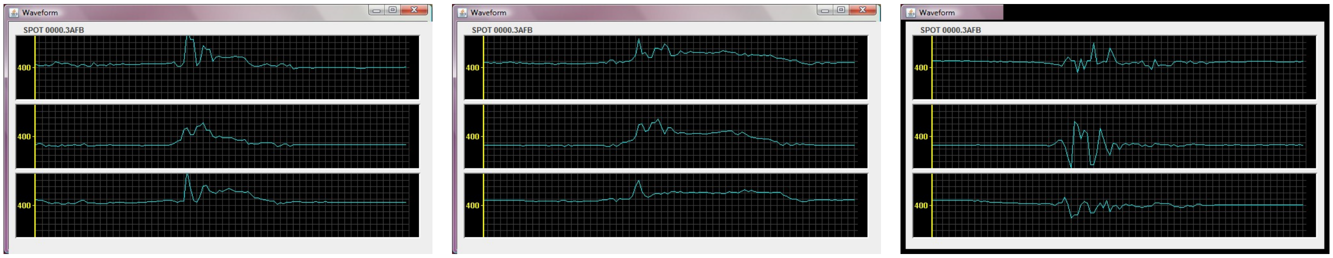
SENSING PLATFORM

For this work, data is recorded using an off-the-shelf programmable sensing platform called Sun SPOT [15] [16]. Sun SPOT has two types of nodes (see Figure 3). The first type is called data acquisition node. Data acquisition node is an integrated sensing platform with on-board computation and wireless communication capability. It integrates a 32-bit microprocessor with 4M flash memory, a 802.15.4 radio, a sensing board, and a battery board. The microprocessor is powerful to perform on-board real-time signal processing. The sensing board not only integrates a collection of built-in sensors, such as a ±2g/6g 3-axis accelerometer, but also provides a standard interface to outfit external sensors. The second type of node is called basestation node. It receives the sensed data transmitted from the remote data acquisition node via wireless radio and passes the data to a wired workstation for back-end processing.

In our experiments, only the ±6g 3-axis accelerometer is used. The data acquisition node is programmed to transmit sampled accelerometer data back to the basestation node. The basestation node then passes the data to the workstation (a PC) where a back-end multi-class classifier is implemented to perform real-time activity recognition.

MODEL EVALUATION

To evaluate the performance of our Bayesian network model for context-aware fall detection, we first examine the accu-



(a) The acceleration data for a backward fall (b) The acceleration data for lying down backward (c) The acceleration data for jumping

Figure 4. The 3-axis acceleration data for fall (a), lying down backward (b), and jump (c)

racy and false positive rate of an isolated fall detection algorithm without any context information involved. Then, we show some specific inference results generated from our Bayesian network model when complete and partial context information are available respectively. Finally, we examine the performance of our fall detection system by running a real-world continuous monitoring test.

Isolated Fall Detection Result

We use a multi-stage thresholding algorithm similar to [2] based on the acceleration data as our isolated fall detection algorithm. We choose this algorithm since it is easy to implement and computationally efficient. For experiment setup, a single data acquisition node is attached to the test subject's front waist. The sampling rate for the accelerometer is set to 100Hz. Four types of falls {*forward*, *backward*, *leftward*, *rightward*} and four activities of daily living {*walk*, *jump*, *lie down*, *sit and stand*} are considered. Each type of activity is performed 30 times. The worst case fall detection rate and false positive rate are 93.3% {*fall leftward*} and 60% {*lie down*} respectively. Although this simple isolated fall detection algorithm achieves a near perfect fall detection rate, it suffers from a very high false positive rate. This is because *lie down* has a very similar signal shape compared to fall. This is illustrated in Figure 4.

Specific Inference Examples

In this section, we take the context information into consideration, and evaluate our Bayesian model by showing results produced by the inference algorithm. We first evaluate our model by assuming we have a complete observation of all the context information. Then we examine the cases in which only partial observations are available.

Inference with Complete Observation

Assume all the context information incorporated in our model is available. Here we show the inference results in four scenarios that correspond to true positive rate, true negative rate, false negative rate, and false positive rate respectively. The results are summarized in Table 1.

To calculate the true positive rate, consider the situation of an elderly subject over 65 walking on the street. A sudden large blood pressure drop is sensed and a temporary activity limitation is detected after the isolated fall detection algorithm gives its alarm. If we denote the variables in Figure 2 by their initial letters, the query is expressed as $P(F|H, I, S, L, Y, T, A)$. Following the local Markov property of the Bayesian network, the query can be factored and calculated as

	Probability
True Positive Rate	95.2%
True Negative Rate	99.76%
False Negative Rate	68.5%
False Positive Rate	1.34%

Table 1. Probabilities with complete observation

$$\begin{aligned} P(F|H, I, S, L, Y, T, A) &= \alpha \cdot P(F, H, I, S, L, Y, T, A) \\ &= \alpha \cdot P(H) \cdot P(I|H) \cdot P(Y) \\ &\cdot P(S|I) \cdot P(L) \cdot P(F|Y, S, L) \\ &\cdot P(T|F) \cdot P(A|F) \end{aligned} \tag{3}$$

where α is the normalization factor, which can be determined by calculating $P(\neg F|H, I, S, L, Y, T, A)$ in the same way. That is,

$$\begin{aligned} P(\neg F|H, I, S, L, Y, T, A) &= \alpha \cdot P(\neg F, H, I, S, L, Y, T, A) \\ &= \alpha \cdot P(H) \cdot P(I|H) \cdot P(Y) \\ &\cdot P(S|I) \cdot P(L) \cdot P(\neg F|Y, S, L) \\ &\cdot P(T|\neg F) \cdot P(A|\neg F) \end{aligned} \tag{4}$$

where

$$P(F|H, I, S, L, Y, T, A) + P(\neg F|H, I, S, L, Y, T, A) = 1 \tag{5}$$

To calculate this posterior probability, we use the worst case fall detection rate and false positive rate in Section as $P(A|F)$ and $P(A|\neg F)$. All other prior and conditional probabilities are based on the medical research results in Section . And we assume those results can be applied to a general elderly population. The calculated posterior probability of fall is 95.2%, which matches the isolated fall detection algorithm results reasonably well. For true negative rate, the query $P(\neg F|H, I, \neg S, L, Y, \neg T, \neg A)$ is considered. The calculated posterior probability of fall is 99.76%.

The third query we consider is $P(F|H, I, S, L, Y, T, \neg A)$. That is, although both the pressure drop and activity limitation are sensed, the alarm somehow does not occur. The calculated posterior probability of fall is 68.5%, which is as twice as the case when fall does not occur. This result indicates that the false negative rate can be improved with the help of context information.

Finally we consider the query $P(F|H, I, \neg S, L, Y, \neg T, A)$ in which the alarm occurs but neither pressure drop is sensed nor the temporary activity limitation is detected. This is very similar to the activity *sit and stand* in which the isolated fall detection algorithm suffers from a high false positive. In this case, the probability of fall inferred from our model is 1.34%, which indicates that context information can play a significant role in reduing the false positive rate.

Inference with Partial Observation

In many cases, not all the context information is available due to sensor failure, noise, and power limitation. In such cases, marginalization over all unobserved variables is performed. For example, assume we only get to know the motion sensor (accelerometer) data from which we can interpret the subject's physical activity and the result of the isolated fall detection algorithm. Based on this partial observation, the posterior probability of fall is calculated as

$$\begin{aligned} P(F|Y,T,A) &= \alpha \cdot \sum_{H,I,S,L} P(F,H,I,S,L,Y,T,A) \\ &= \alpha \cdot \sum_{H,I,S,L} P(H) \cdot P(I|H) \cdot P(Y) \\ &\cdot P(S|I) \cdot P(L) \cdot P(F|Y,S,L) \\ &\cdot P(T|F) \cdot P(A|F) \end{aligned} \tag{6}$$

where α is again the normalization factor.

To make a full comparison with the complete observations cases, we also calculate the inference results in the same four scenarios when only partial observations are available. The results are listed in Table 2. As shown in the table, the true positive rate, the true negative rate, and the false negative rate are close to the corresponding result when full observation is available. For the false positive rate, the probability of fall increases from 1.34% to 21.43%. This result indicates that with only the subject's physical activity context information, the certainty of a subject not falling is reduced.

	Probability
True Positive Rate	94.4%
True Negative Rate	93.69%
False Negative Rate	55.71%
False Positive Rate	21.43%

Table 2. Probabilities with partial observation

Context-Aware Fall Detection Results

In this section, the subject is asked to wear an additional data acquisition node on his left ankle (see Figure 3) which is responsible to recognize the subject's current physical activity status. As a proof of concept study, physiological sensors and location sensors are not included in this experiment. In order to identify the subject's physical activity, a multi-class SVM classifier is trained to differentiate walking, running, lie still, and standing still. The classification result (the subject's physical activity) along with the result of the isolated fall detection algorithm together are imported to the inference engine. A fall is detected if the inference probability is over 50%. Three subjects get involved in this experiment. Each subject is asked to perform four actions: (1) *Walk and fall and lie still*, (2) *Walk to a bed and lie down on the bed*, (3) *Walk to a sofa and sit down*, (4) *Stand up from a sofa and jump*. Each action is performed 10 times per subject. The fall detection results are shown in Table 3.

Activity	Fall detection rate
Walk and fall and lie still	93.3%
Walk to a bed and lie down on the bed	83.3%
Walk to a sofa and sit down	16.7%
Stand up from a sofa and jump	0%

Table 3. Context-aware fall detection performance

As illustrated in the Table 3, our context-aware fall detection system works reasonably well in action (1), (3), and (4). However, it fails to differentiate the action (2) from fall. We believe this can be improved if the subject's physiological condition context information is incorporated.

CONCLUSION AND FUTURE WORK

In this paper, we have demonstrated the feasibility of using context information, specifically, the physicial activity information, to help an isolated fall detection algorithm reduce both false negative and false positive rates using a Bayesian network. For future work, one topic is to incorporate physiological and location information to give a full evaluation on our integrated fall detection framework. For the other topic, because our Bayesian network is purely hand-constructed based on common senses and medical research results, it is by no means a final answer to the problem of fall detection. Therefore, we will explore methods to learn the structure of the Bayesian network automatically in a data-driven manner and compare the results with the hand-constructed one.

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