Journal of Mobile Multimedia, Vol. 9, No.1&2 (2013) 015-026

A WEARABLE SENSOR BASED APPROACH TO REAL-TIME FALL DETECTION AND FINE-GRAINED ACTIVITY RECOGNITION

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We present a real-time fall detection and activity recognition system that is inexpensive and can be easily deployed using two Wii Remotes worn on human body. Continuously 3-dimentional data streams are segmented into sliding windows and then pre-processed for removing signal noises and filling missing samples. Features including Mean, Standard deviation, Energy, Entropy, Correlation between acceleration axes extracted from sliding windows are trained the activity models. The trained models are then used for detecting falls and recognizing 13 fine-grained activities including unknown activities in real-time. An experiment on 12 subjects was conducted to rigorously evaluate the system performance. With the recognition rates as high as 95% precision and recall for user dependent isolation training, 91% precision and recall for 10-fold cross validation and as high as 82% precision and recall for leave one subject out evaluations, the results demonstrated that the development of real-time, easy-to-deploy fall detection and activity recognition systems using low-cost sensors is feasible.

Key words: Activity recognition, fall detection, wearable sensors

1. Introduction

Falls are one of the most high-risk problems for old people. A study conducted by the Centers for Disease Control and Prevention [8] shows that up to 33% adult people aged over 65 falls at least once a year. Of which about 30% cases cause medium to severe injuries that can lead to death. Moreover, people aged over 75 who fall more likely four to five times than those age 65 to 74 to be admitted to a long-term care facility for a year or longer [23]. In addition to the elderly, disable people such as people with dementia, Parkinson or poor motor control also significantly contribute to falls. For example, there are as many as 400 falls per 100 dementia people [31]. Injuries caused by falls can be obstacles on the elderly's living independent at homes, and increase the risk of early death. This is a seriously obstacle on the elderly's living independent at homes. Although there are a number of previous studies on fall detection and yielded significant results (i.e. accuracy of 80-90%), in fact falls might occur while the elderly performs daily life fine-grained activities such as walking, jumping, going-up stairs, going-down stairs, running, etc. The information of such activities can provide warning the elderly for preventing the falls (i.e. jumping or running might highly cause a fall). Moreover, daily activity information can not only be a fundamental element for situated services to support people [19, 32], but also be useful for health and energy expenditure monitoring [2]. The development of system integrated both activity recognition and fall detection using low-cost technologies at people's homes has real potential to provide age-related impaired people with a more autonomous lifestyle, while at the same time reducing the financial burden on the state and these people and their families.

Majority of existing wearable activity recognition systems and fall detection systems require specific hardware and software design which often cost hundreds of US dollars or more. Meanwhile, pervasive sensing deployment often requires many sensors in the environmental surroundings [2], which might exceed the budgets of the poor and middle-class people. This is especially true in Vietnam where up to 29% of Vietnamese population is classified as poor or below (according to the UNDP standard [10]). Therefore, proposing a low-cost sensor and easy deployment technology for prototyping the fall detection and activity recognition system is a key component of this study to make the pervasive computing technologies support people's lives and help the elderly even low-income people to live more independent at their homes.

Our main contribution is twofold:

First, we prototype a fall detection and activity recognition system that can automatically detect human falls and can recognize 13 fine-grained human activities including unknown activities in real-time. Our work is distinct from other works on activity recognitions [4, 12, 15, 35] as we address a set of fine-grained activities (rather than high-level activity set) and utilize the use of easily deployable and low-cost wearable sensors. The sensing devices used in the system are inexpensive and available on the market.

Second, we evaluate our system on an open-dataset (i.e. including unknown activities) that we collected from 12 subjects who performed 13 activities and 144 falls at their homes under individual training, 10-fold cross validation and leave-one-subject-out protocols.

2. Related work

2.1. Activity recognition

Two common approaches to activity recognition are computer vision based and sensors based. In the first approach, computer vision technology is used to analyze the video streams from digital cameras installed in the environments (i.e. [6, 35]) to infer human activities. Even though, many research works have good results in the laboratory but they fail in real-home deployment due to their dependence on the environmental conditions such as light condition, clutter and highly varied activities. Those also have to deal with changes in environmental conditions during the day that makes the problem more complex. In the second approach, activity recognition is performed by analyzing the streaming data from sensors. A variety of sensors are used to recognize user activity including accelerometer, audio, gyroscope, etc. Sensors can be embedded into objects [19, 20], environments [4, 27], or worn on different parts of human body [2, 3, 12, 22].

Previous works such as Bao and Intille [3] used 5 accelerometers worn on different body's parts to recognize user physical activity like walking, sitting, standing still, watching TV, running, bicycling, eating, reading etc. Sensor data was combined for classifying the activities with overall accuracy of 84%. Work by Van Laerhoven et al. [29] even used 30 accelerometers spread across the body to enhance the recognition rates of a relatively complex dataset of activities. Other works [9, 28] developed an activity recognition system that can distinguish forms of locomotion and postures like sitting, standing, walking, ascending and descending a stairway. Most of these works deployed the sensors that are used in laboratory (i.e. MITes [3]) or relatively expensive sensors. Moreover, in addition to recognizing activities as these works, we propose a recognition method not only to classify user activities but also to detect falls in real-time to assist the elderly.

In this study, we focus on inexpensive sensors that can be worn on different parts of human body as cameras installed in the environments might raise issues concerning confidentiality and privacy invasion. Among sensing devices available on the market we choose Wii Remotes as they are cheap and easy in deployment. Wii Remote has the ability to sense acceleration along three axes through the use of an ADXL330 accelerometer [33]. In our work, users wear such accelerometers on hip and wrist to perform everyday fined-grained activies. Previously, Wii Remotes were also used for recognizing food preparation activities [20, 37].

2.2. *Fall detection*

Some past researches addressed fall detection and activity recognition problem (i.e. [18]) using cameras but they lack flexibility as these often require the pre-settings of the environments such as camera positions and calibrations. They are also case specific and dependent on different scenarios, therefore only small areas can be tracked. Moreover, those approaches possibly invade confidentiality and privacy.

Many fall detection systems based on smart-phone such as [1, 25] to utilizes the acceleration data from accelerometers integrated inside the phone. Although those studies have significant results (~90% accuracy), it is noticed that falls often occur while people are doing other activities such as jumping, running, going-up stairs, going-down stairs, etc. Some of them might lead to the elderly fall. To our knowledge, no existing studies explored the recognition a set of low-level activities and detection of falls using low-cost sensing technologies with real-time implementation.

A small number of fall detection systems utilize the fusion of accelerometer and other sensors to achieve high accuracies of fall detection. In [13], Hwang et al. used a tri-axial accelerometer and gyroscope, both placed on the chest and Lai et al. in [16] combined several tri-axial accelerometers for joint sensing of injured body parts, when an accidental fall occurs. Inertial sensors and the data logging unit are combined by Wu et al. [34] to develop a portable pre-impact fall detection system. In this paper, we conducted with only two accelerometers (in Wii Remotes) worn on wrist and hip of the body to effectively detect falls while still recognizing other 13 user activities.

A majority of prior works on fall detection are conducted using classification method. Doukas et al. in [5] proposed an Support Vector Machines (SVM) based system to detect falls from running activity. Jantaraprim et al. [14] also used SVM with a proposed feature called short time min-max to distinguish fall from activities of daily living. Zhang et al. [36] demonstrated a mobile-phone based fall detection system using 1-class SVM classifier. In general, these works achieve high fall detection rates (i.e. over 95%). However, comparing to our dataset, their datasets are significantly simpler and less (or no) noisy. In this work, we propose a HMM based classifier for both fall detection and activity recognition, but our work is distinct from others as our dataset collected from 12 subjects and each subject perform 12 falls with various postures and other 13 daily activities in which some activities are pretty similar to falls such as standing-to-sit, sitting-to-lie, etc., and we extract a new feature set effectively for considerably improving detection rates.

3. Hardware

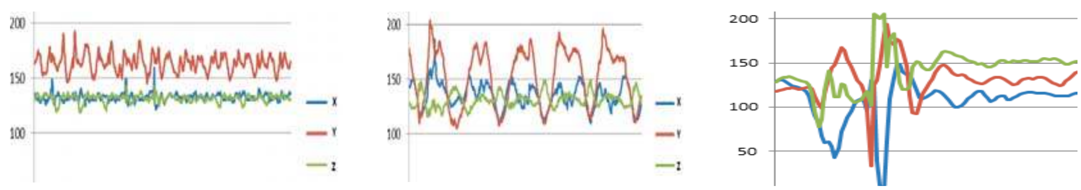
In contrast to most of accelerometers often used in research labs (i.e. [3, 10, 12, 22]) or on the market but relatively expensive (i.e. [17, 26, 31]), or complex deployment (i.e. requires base-station for communication to the computer), Wii Remotes are relatively cheap, available on the market, and simple in deployment as Wii Remote communicates with the computer via a Bluetooth dongle. Both Wii Remote and Bluetooth dongle are inexpensive and are available in Game stores.

The Wii Remote [33] is a consumer off-the-shelf wireless sensing system and games controller which supports two functionalities relevant to our application: (i) input detection through an embedded accelerometer; and (ii) data communications through Bluetooth. A Wii Remote comprises a printed circuit board (which is encapsulated by a white case) and uses an AXDL 330 accelerometer [2] and a Broardcom BCM2042 chip that integrates the entire profile, application, and Bluetooth protocol stack. Based on Micro Electro Mechanical System (MEMS) technology, the AXDL 330 accelerometer is a small, low power, 3-axis accelerometer with signal conditioned voltage outputs. The AXDL 330 accelerometer can sense acceleration in three axes with a minimum full-scale range of ±3g. While the static acceleration of gravity can be used to implement tilt-sensing in applications, dynamic acceleration measurement can be detected through the quantifiers of motion, shock or vibration.

The Broadcom BCM2042 board is a system-on-chip which integrates an on-board 8051 microprocessor, random access memory/read only memory, human interface device profile (HID), application, and Bluetooth protocol stack. Furthermore, multiple peripherals and an expansion port for external add-ons are embedded on the board. The integration of these components and the technology's adoption in a mass market consumer games console has significantly reduced the cost of BCM2042. The Wii Remote's input capabilities include buttons, an infrared sensor and an accelerometer. The infrared sensor is embedded in a camera which detects IR light coming from an external sensor bar. The accelerations are measured in X, Y, and Z axes (relative to the accelerometer) and the three directions of the movement (X, Y, Z) can be computed through tilt angles. Wii Remote inputs and sensor values are communicated to a Bluetooth host through the standard Bluetooth HID protocol. Values for acceleration are transmitted with a sampling frequency of 100Hz (100 samples per second).

In this study, subjects were asked to worn 2 Wii Remotes: one worn on hip and the other worn on right-hand's wrist. While the sensor worn on hip can provide good features for the detection of falls, and running, walking, going-up stairs activities, the sensor worn on wrist might be useful for recognizing activities performed with hand such as cleaning, typing, and brushing. We will use the combination of both sensing data streams from 2 sensors for the detection of falls and recognition of activities.

Figure 1. Wii Remote worn on wrist (left) and Wii Remote worn on hip (right)



Cleaning *Stretching* *Falling*

Figure 2. Examples of accelerometer signals for three human activities and falls

4. Real-Time Fall Detection and Activity Recognition

The real-time Fall Detection and Activity Recognition (FDAR) algorithm works in 4 steps:

- Signal processing: sensing data is filtered for removing the noise or re-sampling the lost data.
- Segmentation: a sliding window/frame is used to segment the signal stream into frames of fixed length.
- Feature extraction: from each frame, different features are extracted.
- Classification: the system uses the features extracted from the previous step as input for a HMM based classifier.

In the following sections, we describe each of these steps in detail.

4.1. Signal processing

Sensing data from sensors are often noisy and ambiguity. Ideally, at a sampling frequency of 100Hz, each second the sensor yields 100 samples of X, Y, Z acceleration triplets (i.e. one sample per 10 mili-seconds). In practice, many real-world factors such as metallic items placed between the sensors and the receiver, sensors are unintentionally dipped into water, etc. might mean that some samples are lost or dropped whistle abnormal human movements (i.e. a tap with hand) might also cause abnormal sensing data. Furthermore, the sensors themselves can yield noisy readings (e.g. too large or small values). In such cases, a filter is applied to remove noise and to fill out lost samples. In this step, the data filter performs both a low-pass filtering for removing abnormally low sample values and a high-pass filtering for removing abnormally high sample values. After that, samples are grouped into sliding windows or frames. If a frame contains less that 75% of its full complement, it is discarded on the grounds that there is insufficient information to classify activities. Otherwise, it is re-sampled using a cubic spline interpolation method [24] to fill out the lost samples.

Along with acceleration X,Y,Z, we compute pitch, roll for each triplet:

$$Pitch = 2\ arctan\left(\frac{y}{\sqrt{x^2+z^2}}\right) \tag{1}$$

$$Roll = 2\ arctan\left(\frac{x}{\sqrt{y^2+z^2}}\right) \tag{2}$$

where x, y, z are acceleration values of the three axes.

4.2. Segmentation

Previous studies showed that the length of sliding window has significantly impact on the performance of the pattern recognition algorithms [3, 20]. In this study, we did a pilot study on the subset of collected dataset for selecting a reasonable length for sliding window. We varied the window length 1 second, 1.2 second, 1.5 seconds, 1.8 seconds, 2 seconds and 2.5 seconds and we stick on the window length of 1.8 seconds. The reason for the choosing window length of 1.8 second is that this length allows avoiding delay from continuously real-time processing while providing a reasonable recognition rate.

4.3. Feature Extraction

For each frame of size n where n is number of time points, the following features are extracted:

$$Mean(x) = \frac{\sum_{i=1}^{n} x_i}{n} \tag{3}$$

$$Standard\ deviation(x){:}\ \delta_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^2) - [Mean(x)]^2} \tag{4}$$

$$Energy(x) = \frac{\sum_{i=1}^{n} x_i^2}{n} \tag{5}$$

$$Entropy(x) = -\sum_{i=1}^{n} p(x_i)\log(p(x_i)) \tag{6}$$

where x_i is an acceleration value; $p(x_i)$, a probability distribution of x_i within the sliding window, can be estimated as the number of x_i in the window divided by n.

$$Correlation(X,Y) = \frac{\text{cov}(x,y)}{\delta_x \delta_y} \tag{7}$$

in which cov(x,y) is covariance and δ_x , δ_y are standard deviations of x and y.

Peak/bottom acceleration: for each sliding window, we also extracted 3 peak values and 3 bottom values of acceleration.

These features are combined into a 58-dimentional feature vector, composed of *Mean X, Standard deviation X, Energy X, Entropy X, Mean Y, Standard deviation Y, Energy Y, Entropy Y, Mean Z, Standard deviation Z, Energy Z, Entropy Z, Mean Pitch, Standard deviation Pitch, Energy Pitch, Entropy Pitch, Mean Roll, Standard deviation Roll, Energy Roll, Entropy Roll, Correlation XY, Correlation YZ, Correlation ZX, peak value of X, peak of Y, peak of Z, bottom of X, bottom of Y,* and *bottom value of Z*. These feature vectors are then used for training the pattern recognition algorithms. In the next section, we present the hidden Markov models [16] that we employed for real-time fall detection and activity recognition.

4.4. Hidden Markov Model-based Classifier

In brief, a hidden Markov model [21] is a stochastic model that can be used to characterize statistical properties of a sensing signal. An HMM is associated with a stochastic process not directly observable (i.e. hidden), but it can be observed indirectly through a set of other outputs. The key problem is to determine the hidden parameters given a model and observed parameters. Then, the extracted model parameters can be used to perform further analysis in future learning. An HMM is based on the Markov assumption that the current state depends only on the preceding state.

In our domain, we use HMMs with a mixture of Gaussians of for state's observation distribution. We train one HMM for one activity. The number of hidden states is manually tailored for each model. For example, falling activity model is constituted from two hidden states, while going-up stairs model consists of 5 hidden stages.

In the training phase, the parameters of each model (i.e. initial state probabilities, state transition probabilities, observation probability distribution) were estimated using the Baum-Welch algorithm (implemented in Murphy's HMM Toolkit [15]). After that, we use the trained models for classifying the falls and activities. The Viterbi algorithm is implemented and is used for the computation of the log likelihood probability of each observation sequence O (i.e. a feature vector computed from a continuous sliding window) given the trained model. The classifier will choose the model that produces the maximum log likelihood given feature vectors computed from test data.

5. Experimental Evaluation

5.1. Data collection and annotation

Twelve students from our institute (Posts & Telecommunications Institute of Technology) were recruited, each wore 2 Wii Remotes, one on wrist and the other on hip. Each student was asked to perform 12 activities including walking, jumping, going-up stairs, going-down stairs, running, stretching, cleaning, typing, standing-to-sit, sitting-to-stand, brushing teeth, vacuuming and 12 (intentional) falls with various postures. No order of performing activities is required and no time constraint to each activity performed by the subject. Each activity is required to be performed as naturally as possible. In addition to sensing data, we recorded videos of subjects performing the activities.

To synchronize between the collected videos and the accelerometer data from Wii remotes, at the beginning time of each session the subject was asked to shake the body and the hand 3 times to make distinct signals. The subject was apparently shown on the videos. In addition, along with each sample, a timestamp was written to the acceleration data log files.

The subjects were given a list of 12 labels of activities to annotate the collected videos using ELAN Multimedia Annotator Tool [7]. Movements that are not one of 12 activities and falls were automatically labelled with "unknown".

5.2. Performance metrics

Recognition results are reported as frame-wise precision, recall and F-measure values. The *precision* for an activity was calculated by dividing the number of correctly classified frames by the total number of frames classified as being a particular activity (i.e. *true positives/(true positives + false positives)*). Recall was calculated accordingly as the ratio of the number of correctly classified frames to the total number of frames of an activity (i.e. *true positives/total number of frames of an activity*). And, F-measure is the harmonic mean of precision and recall.

5.3. Results for User Dependent Isolation Evaluation

Under User Dependent Isolation Evaluation protocol, the data of each subject is individually trained and tested. Both training data and testing data are from the same subject. Then, the process is repeated for all 12 subjects and the results are averaged. The results are shown on the Table 1. This evaluation is useful for the system that can adapt to the individual's personalized behaviors.

Overall, precision, recall, and F-measure are over 93% for user dependent isolation (i.e. subject dependent) analysis. Majority number of activities including falls has precision and recall as high as over 95% except for *stretching* and *sitting-to-stand* activities. While *stretching* is often misclassified as *cleaning*, *sitting-to-stand* is misclassified as *standing-to-sit* and *falling*. The recognition rate of *falling* in this case is 96% precision and 95% recall.

Table 1. User Dependent Isolation Evaluation results (numbers are in percent)

Activity	Precision	Recall	F-measure
brushing teeth	96.17	92.09	94.09
Cleaning	95.25	94.73	94.99
Falling	96.53	95.14	95.83
going-down stairs	95.37	94.91	95.14
going-up stairs	97.44	97.86	97.65
Jumping	98.99	97.98	98.48
Running	98.84	99.13	98.98
sitting-to-stand	92.81	90.42	91.6
standing-to-sit	96.1	92.86	94.45
Stretching	90.41	86.76	88.55
Typing	98.2	97.69	97.94
Vacuuming	98.75	98.34	98.54
Walking	97.37	95.15	96.25
Unknown	91.39	88.1	89.71
Average	**95.47**	**93.7**	**94.58**

Table 2. 10-fold cross validation results (numbers are in percent)

Activity	Precision	Recall	F-measure
brushing teeth	94.64	90.56	92.56
Cleaning	89.98	82.43	86.04
Falling	93.06	91.67	92.36
going-down stairs	96.76	93.06	94.87
going-up stairs	98.72	95.3	96.98
Jumping	98.48	97.98	98.23
Running	97.39	96.52	96.95
sitting-to-stand	87.43	89.22	88.32
standing-to-sit	96.75	94.16	95.44
Stretching	76.71	69.41	72.88
Typing	96.4	95.89	96.14
Vacuuming	97.92	97.51	97.71
Walking	96.77	95.35	96.05
Unknown	86.17	86.63	86.4
Average	**92.58**	**90.54**	**91.55**

5.4. Results for 10-fold Cross Validation

Under 10-fold cross validation procedure, the dataset was randomly partitioned into 10 parts of equal size. Nine of them are used for training and the remaining one is used for testing. Then, the process is repeated for all 10 parts and the results are averaged. The results are shown on the Table 2. Note that both training and test sets may contain data from the same subject.

Overall, precision, recall, and F-measure are over 90% for 10-fold cross validation (i.e. subject dependent) analysis. Majority number of activities including falls has precision and recall as high as over 90% except for *stretching* activity which is often misclassified as *cleaning*. It is noticed that the recognition rate of *falling* is 93% precision and 91.6% recall.

5.5. Results for Leave-One-Subject-Out Evaluation

In addition to 10-fold cross validation which is often used for systems for personal use or adaptation. We envisage to evaluate the system under the *leave-one-subject-out* protocol. In which, we used 11 subjects for training and left the remaining one for testing. The process was repeated for all 12 subjects, and the results were averaged. Table 3 shows the results. It is noticed that the tested subject was not included in the training data.

Table 3. Leave-one-subject-out results (numbers are in percent)

Activity	**Precision**	**Recall**	**F-measure**
brushing teeth	85.71	86.99	86.35
Cleaning	81.2	77.5	79.31
Falling	84.03	82.64	83.33
going-down stairs	91.67	84.72	88.06
going-up stairs	94.44	90.17	92.26
Jumping	97.47	96.46	96.96
Running	96.23	93.91	95.06
sitting-to-stand	73.65	74.85	74.25
standing-to-sit	78.57	77.92	78.24
Stretching	64.38	63.93	64.15
Typing	95.37	95.12	95.24
Vacuuming	96.05	85.45	90.44
Walking	95.15	88.89	91.91
Unknown	72.25	70.51	71.37
Average	**85.2**	**82.16**	**83.65**

The overall recognition rates for *leave-one-subject-out* evaluation are 85% precision, 82% recall, and 83.6% F-measure, which are lower than those of *10-fold cross-validation*. Note that, *leave-one-subject-out* is more difficult than *cross-validation* because the system has to recognize activities for unseen subjects. This setting is also more similar to practical conditions where a system trained on a set of subjects is used to make recognitions for new subjects, data about which are unknown at training time. Again, *stretching* proved to be the most difficult activity to recognize with the F-measure as low as 63% while for *running*, *jumping*, and *typing* the system achieved F-measures higher than 90%. This is consistent with *10-fold cross validation* results. This evaluation is useful for the system that needs pre-trained models for detecting falls and recognizing activities (i.e. models are trained with off-line collected data, and then use for real-time detection and recognition).

6. Conclusion

We have presented a solution for detecting falls and recognizing 13 other human activities. Our method uses inexpensive sensing devices such as Wii Remotes worn on human body as sources of signals, thus provides a low-cost solution. From accelerometer signals, the system extracts several types of features that summarize different aspects of movements. A hidden Markov model is used to map these features into hidden states, which corresponds to different activities. An empirical study with data collected from 12 subjects demonstrates the effectiveness of the proposed method. The system achieved average F-measures of 94.5% for user dependent isolation, 91.55% for 10-fold cross-validation and 83.6% for leave-one-subject-out settings respectively. With relatively high accuracy while being simple and inexpensive, the proposed solution can be used for practical applications requiring the recognition of human activities.

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