Indoor Fall Detection Using a Network of Seismic Sensors

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***Abstract*—Falls present a great health threat as people get older, and it has been shown in studies that rapid response is critical to decreasing fall-related mortality. Thus, the development of signal processing algorithms for biomedical applications involving assisted living has become an avid area of research. In this work, a novel algorithm for activity classification and fall detection using a seismic sensor network is proposed. More specifically, classification of falling as well as sources of parasitic signals, such as dropping an object, slamming a door, and shutting a window, are considered. A new target detection and feature extraction algorithm based on wavelet coefficient characterization and spectral statistics is proposed. Results quantifying the performance of the algorithm on real data from a seismic sensor network are given. It is shown that the algorithm offers a reduction of false alarms especially in the case of potentially confusable parasitic signals.**

Keywords—fall detection; human activity; seismic sensor network; classification.

I. INTRODUCTION

Human activity recognition is an important area of research with critical application to support the assisted living and remote health monitoring of elderly and disabled people. As people get older, their bodies go through multiple physical changes making them more fragile, and more prone to falls. The number of elderly people treated for fall related injuries in emergency rooms is increasing each year [1]. The most common consequences of those injuries are fractures, loss of independence or even death. Smart environments are typically equipped with a sensor network comprised of several different types of sensors, which enable the measurement various physiological and biomedical signals indicative of personal health. Human gait is one such signal, and may be used to recognize the activities of the patient or individual being monitored. Here, the aim is to distinguish normal daily activities, such as walking and running, from gait patterns that could be a sign of distress, such as falling, limping, seizures, or extended durations of motionlessness. Human activity recognition techniques can be used to detect falls of the elderly or people in need of care, which will result in quicker response by care providers.

This work focuses in particular on fall detection, which may be ascertained by a variety of different sensors, such as

- Video Camera: One or multiple cameras recording activities in the environment may be employed with image processing techniques to identify human motion patterns [2,3]. However, the use of cameras has strong disadvantages, especially in a home environment, due to unavoidable infringement of privacy, especially in the bedroom and bathroom areas.
- Environment sensors: Multiple sensors, such as acoustic, radar, and seismic sensors, are placed at a fixed location to classify motion. Of these sensors, however, acoustic sensors also pose a privacy problem due to the potential to record all conversations, as well as the potential for a variety of sounds and noises to contaminate the data. Radar has the disadvantage of being highly sensitive to the angle at which the person approaches the sensor – tangential motions are not sensed. Moreover, objects within the room may occlude the desired return. On the other hand, seismic sensors are not much affected by objects along the line of sight, since seismic waves can propagate through the floor.
- Wearable sensors: Wearable sensor systems are based on accelerometers placed on the subject [4,5,6]. The main disadvantage of this kind of solution is that wearing them may not be convenient and elderly people may forget to put on or carry the sensor, rendering it useless.

There have been studies on the use of sensors for tracking elderly or people in need of care by placing different sensors in their living environment [7,8,9,10,11,12,13], as well as studies on footstep detection specifically with seismic sensors [14,15,16,17].

In this paper, a seismic sensor network is used for indoor fall detection and activity monitoring. Multiple sensors are employed in each corner of a room for human fall detection. A noise cancelling amplifier is utilized to improve data quality and subsequent processing results. A novel target detection and feature extraction algorithm using wavelet coefficient characterization and spectral statistics is proposed. The proposed algorithm relies on extracting features from wavelet coefficients and the shape statistics of the signal. Shape statistics are used in power spectral analysis and represent the shape of a probability distribution that can model the statistical distribution of a population. Features extracted using the shape statistic show the closeness of magnitude spectrum with respect to normal distribution. The distribution and the energy of the wavelet coefficients are also used as features for classification. It is shown that this approach yields performance robust to potentially confusing sources of parasitic seismic waves, thereby improving classification and fall detection performance.

II. Data Acquisition

Data acquisition systems typically convert analog waveforms into digital values for processing. Data acquisition applications are controlled by software programs developed using various general purpose programming languages. As technology has progressed, this type of process has been simplified and made more accurate, versatile, and reliable through electronic equipment. The USB-1208FS data acquisition device is used in this work for acquiring seismic signals. The USB-1208FS acquires data one analog sample at a time using a software command triggered by computer. The analog value is converted to digital and returned to the computer. The analog data is acquired and converted to digital values until the scan is stopped. USB-1208FS has eight analog input channels that are software-selectable for either eight 11-bit single-ended inputs or four 12-bit differential inputs. The total sample rate for all channels cannot exceed 50kS/s. Four differential input channels are used with a sampling frequency of 12.5kS/s.

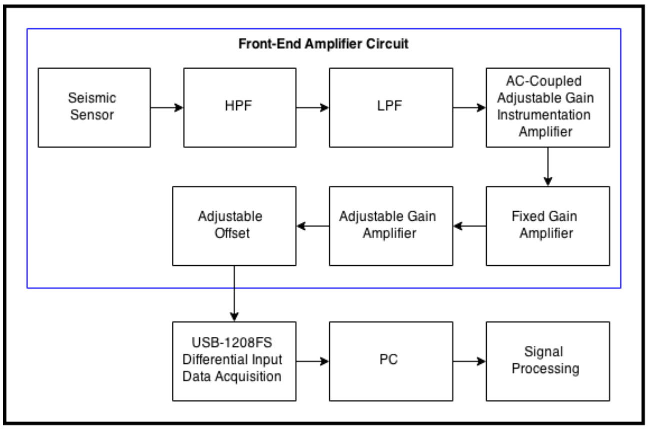

Fig. 1. Stages of the data acqusition and signal processing

III. Methodology

Acquisition of noise-free signals and feature extraction are the most critical issues of this study since they have a significant impact on classification performance. The performance of the classifier mostly depends on the quality of the signal and class discriminatively of feature vectors of different activities. A novel target detection and feature extraction algorithm based on wavelet coefficient characterization, spectral statistics, skewness, kurtosis, discrete cosine transform and shape statistic is used for feature extraction. A total number of 23 features are extracted from recordings.

Fig.3 shows time series data and frequency representation of acquired signals for different activities. By the aid of front-end circuit design, measurements with relatively higher SNR values are obtained, as explained in the next section.

A. Pre-Processing Stage

In order to acquire seismic waves, a seismic sensor uses a geophone. Geophones are passive analog devices, which are typically comprised of a spring-mounted magnetic mass moving within a wire coil to generate an electrical signal.

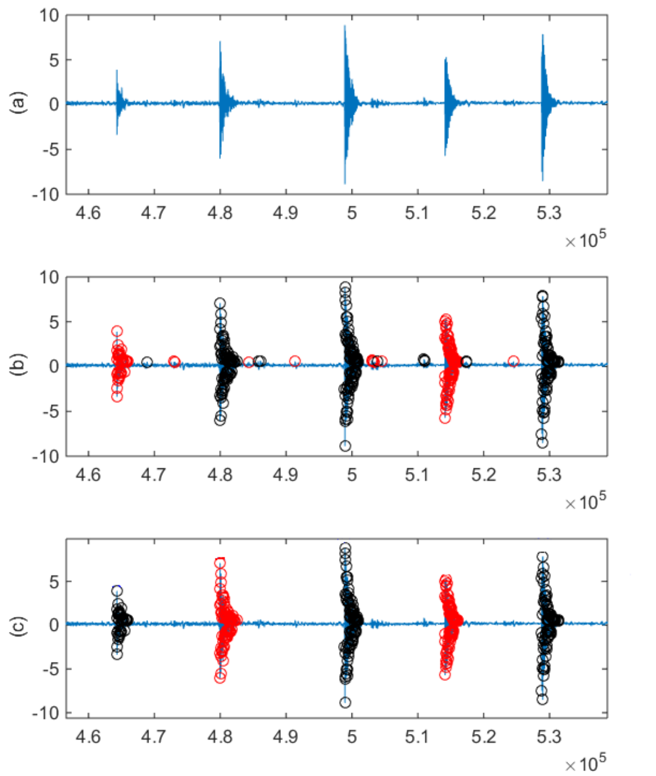

Fig. 2. Noise elimination from time series data; original signal (a), finding peaks and grouping (b), noise elimination and acquiring seismic sign (c).

The frequency response of a geophone is that of a harmonic oscillator, fully determined by corner frequency at around 10 Hz, open loop damping of 0.25 and sensitivity of 28.8 V\m\s. Analog geophones are very sensitive devices, which can respond to very distant tremors. However, the electrical signals might be very small for distant tremors. To keep SNR value high for acquiring those tremors, there has to be a Low Noise Amplifier specifically designed for seismic application. In order to eliminate noise factor, a high pass filter (HPF) and low-pass filter (LPF) are utilized before the instrumentation amplifier circuit. An instrumentation amplifier is a type of differential amplifier which eliminates the need for input impedance matching and thus makes the amplifier particularly suitable for use in seismic applications. Additional characteristics of instrumentation amplifier is a very low DC offset, low drift, low noise, very high open-loop gain, very high common-mode rejection ratio, and very high input impedances. For those reasons instrumentation amplifier implemented as pre-amplifier after filtering process.

Before starting feature extraction process seismic signal signs must be excracted from time series data. A detector algorithm used for detecting seismic signal for feature extraction process shown in Fig.2.

B. Detection

The detection of bona fide seismic signals from time series data is a critical step of seismic signal processing. Often, noise may be confused with signals associated with an event of interest. For this reason, the detection algorithm developed is shown in Fig.2. The algorithm takes as input a seismic signal recorded for a given period of time, as shown in the figure. In the first stage, this algorithm finds peaks of the data that are greater than a defined threshold value and groups them as one group if the peaks are close enough to each other. The black and red colored circles indicate the grouping of seismic signals. However, this does not preclude some of these groupings from in fact being caused by noise. Thus, the final detection stage eliminates groups thought to be related to noise according to the following criteria: if the number of peaks in the group less than a given threshold, or its max peak is less than a threshold, the group is identified as noise. Experiments show that this procedure is successful in detection true seismic events at a rate of nearly 100%.

C. Feature Extraction

Feature extraction is the most critical part of this work. In this work, a new target detection and feature extraction algorithms based on wavelet coefficient characterization and spectral statistics is proposed. Compared to other algorithms, wavelet coefficient characterization synthesizes more information from different frequency domains and generates more robust feature vectors.

1) Spectral Analysis

Spectral analysis is one of the popular methods in signal processing. The basic idea behind the spectral analysis is Fourier transform, which is frequency representation of time series data. Fourier transform states that any waveform can be analyzed as a combination of sine waves of various amplitude, frequency and phase.

Fourier transform is described as (1). Where x(t) is the time series data and f is the frequency.

$$F = S(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi f t} dt \qquad (1)$$

The Fourier transform of a function of time itself is a complex-valued function of frequency. Its absolute value represents the amount of that frequency, and whose complex argument is the phase offset of the basic sinusoid in that frequency.

Seismic signals caused by different activities create different waves. Power spectral density of different activities shown in Fig.3. As it's clearly seen in the figure, every activity consists of different frequency components. Thus, spectral analysis is able to reveal the frequency information of the activity.

2) Skewness

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable. For a unimodal distribution, negative skew indicates that low spectrum values are more likely to appear within the signal spectrum. While positive skewness value indicates that higher spectrum values are more probable than lower spectrum values. The skewness is not strictly connected with the relationship between the mean and median.

$$\gamma = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i-\mu}{\sigma}\right)^3 \qquad (2)$$

Where, (μ) mean, (γ) skewness and (σ) standard deviation of the spectrum of the signal.

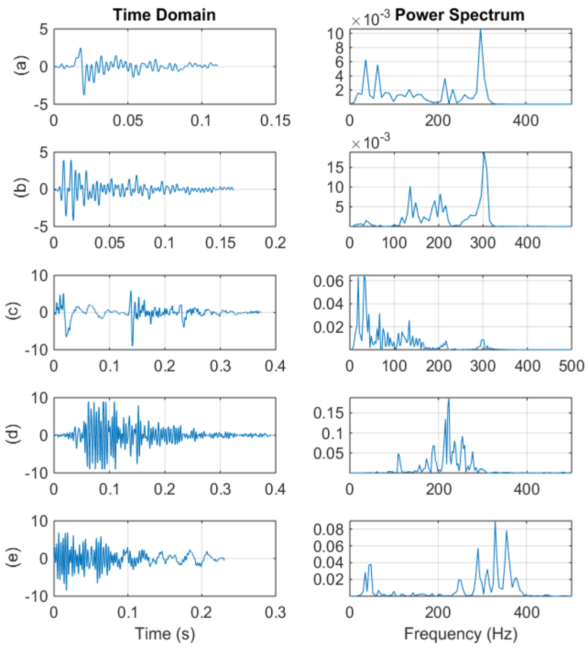

Fig. 3. Time and frequency representation of; walking (a), running (b), falling (c), shutting a window (d), slamming door (e)

3) Kurtosis

Kurtosis is a measure of how peaked or flat the probability distribution a real-valued random variable is. In a similar way to the concept of skewness, kurtosis is a descriptor of the shape of a probability distribution.

$$\beta = \frac{\frac{1}{N}\sum_{i=1}^{N}(X_i-\mu)^4}{\sigma^4} \qquad (3)$$

There are different ways of quantifying for a theoretical distribution and corresponding ways of estimating it from a sample from a population [18]. Kurtosis is computed using the fourth moment.

4) *Wavelet Analysis*

The wavelet transform is designed to analyze non-stationary signals. Wavelet transform is similar to the Fourier transform and more so to the windowed Fourier transform. The main difference is that the Fourier transform decomposes the signal into sine and cosine signals, while the wavelet transform uses functions that are localized in both the real and Fourier space. Unlike the sines and cosines used in Fourier transform for decomposition of a signal, wavelets are generally much more concentrated in time.

First of all, sampled data x[n] goes through high pass filter (H) and low pass filter (G). The output of filters is down sampled by two. The end of the first stage output of the high pass filter becomes wavelet coefficient d_1. The procedure continues until the N'th level decomposition Fig.4.

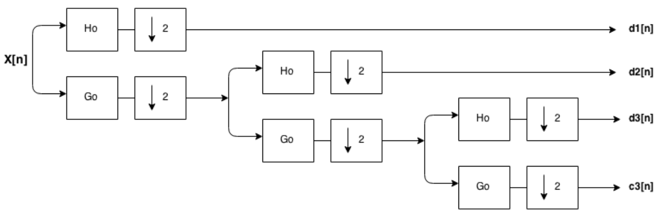

Fig. 4. 3-level decomposition of a signal (Forward wavelet transform). H_0 is an HPF and G_0 is an LPF.

Inverse wavelet transform works in the reverse direction Fig.5.

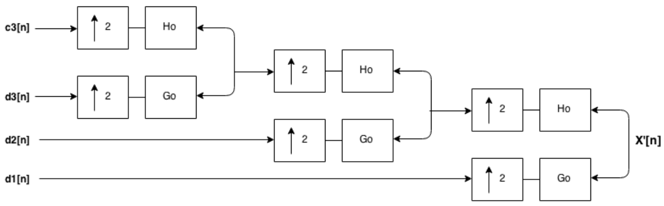

Fig. 5. Reconstrustion of a signal (inverse wavelet transform).

Raw data received from seismic sensors includes unavoidable noises, which affects the performance of the classifiers. Therefore, a denoising process needs to be implemented before feature extraction [19]. A classical approach to removing noise is filtering the input signals. On the other hand, in the wavelet transform the filter results are represented by wavelet coefficients. Thus, the noise effect can be reduced by processing the wavelet coefficients. The SNR of seismic signal is explicitly improved by using a wavelet denoising process. The wavelet analysis is most suitable for seismic detection because of its impulse nature. Wavelet energy is a very effective feature often used in classification problems. Seismic signals of different activities which are seriously contaminated by white noise denoised with a wavelet denosing algorithm. Then, the denoised seismic data is decomposed via discrete wavelet transform algorithms adaptively. The wavelet energy, kurtosis and skewness of each scale are computed.

5) *Discrete Cosine Transform (DCT)*

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of cosine functions at different frequencies. DCT is similar to the discrete Fourier transform (DFT), but using only real numbers.

$$y(k) = w(k) \sum_{n=1}^{N} x(n) cos\left(\frac{\pi}{2N}(2n-1)(k-1)\right), k = 1,2,\ldots,N$$

where,

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}}, & k = 1, \\ \sqrt{\frac{2}{N}}, & 2 \le k \le N, \end{cases} \quad (4)$$

D. *Classification*

There are several types of methods for pattern recognition and classification. One of the most popular classifier is k-nearest neighbor (kNN). This rule classifies an object by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. The principle of the kNN is to estimate this posterior probability directly and then draw the decision rule. Another classification technique is support vector machines (SVM). SVM is a supervised learning classifier formally defined by a separating hyper-plane. The algorithm of SVM simply outputs an optimal hyper-plane which categorizes new examples. SVM algorithm is based on finding the plane that gives the largest minimum distance to the training examples.

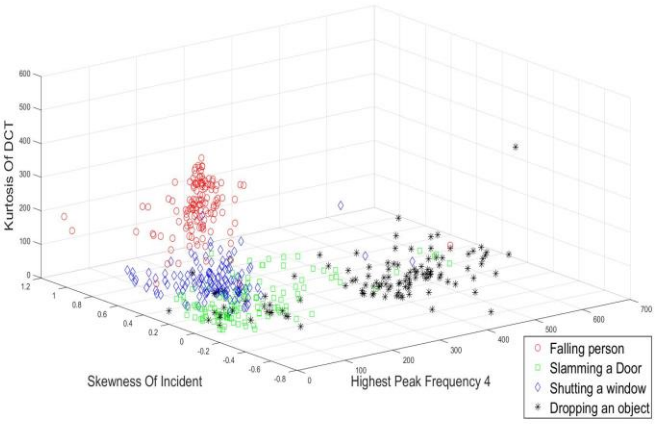

Fig. 6. Distribution of activities such as falling, dropping objects, slamming a door and shutting a window

In the classification process, a training data set and test data set generated from recorded data acquired from seismic sensor for different activities. The training set refers to a set used to derive classifier to determine the parameters of the classifier. The training set divided into two groups as "fall" and "not fall". Then the classifier is used to classify the test data for each sample in the test data set.

IV. Results and Discussions

In the experiments, ten volunteers engaged in 12 repetitions of different activities, such as falling, dropping objects, slamming a door and closing a window. Seismic signals of each activity recorded for a duration of 1 second to form a data base of 120 seismic recordings. The database of seismic signals used for classification is comprised of a total of 1242 recordings. 495 of the recordings are used for tests, and the remaining are used to train the classifier. The classification result after 10-fold cross-validation is given in Table 1. Average results of experiments are described in Table 1 for two different classifiers, support vector machines (SVM) and k-nearest neighbors (KNN). Although the SVM algorithm has lower performance in detecting parasitic seismic events, it has a better performance in fall detection. In order to detect parasitic events, the kNN classifier might be used since it has better performance.

TABLE I. TRUE OR FALSE DECTION NUMBERS USING SVM AND KNN ALGORITHMS

	kNN		***SVM***	
	True	***False***	***True***	***False***
Falling	127	3	129	1
Slamming Door	112	8	113	7
Shutting Window	123	2	99	26
Falling Object	115	5	105	15

V. Conclusion and Future Work

In this paper, the seismic fall detection problem is discussed, and a novel method using wavelet denoising and shape feature extraction methods is proposed. The environment is so complex and changeable that a robust denoising method is essential. In summary, this work offers two key contributions to the area of fall detection with seismic sensors:

1. Seismic sensor data is collected with a lower cost, higher performance hardware system. The design of a noise cancellation amplifier is presented to better cancel noise and improve fall detection performance.

2. Extraction of features from wavelet coefficients and spectral analysis of the signal also yields improved fall detection performance.

The experiment results also showed that both kNN and SVM classifiers are effective in robust seismic fall detection.

For the future work, expanding the data set considering other parasitic signals, such as running, walking and sitting on couch, is planned. Additional features and other classifiers could also be tested.

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