Automatic Fall Detection System using Sensing Floors

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Abstract: *Automatic fall detection is a major issue in taking care of the health of elderly people and has the potential of increasing autonomy and independence while minimizing the risks of living alone. It has been an active research area due to the large demand of the healthcare association for fall detection goods. Fortunately, due to the recent fast progression in sensing technologies, fall detection system becomes prospective. It permits to monitor elders and detect their falls, and consequently provides emergency support whenever needed. This paper describes the current work of detecting falls in independent living apartments using accelerometer concealed under tiles. We present the up-to-date advancement of data collection, feature extraction, feature selection, and signal changing detection, which are essential phases of this work.*

Keywords: *Changing Detection; Elderly Fall Detection; Feature Extraction and Selection; Sensing Floor.*

1. Introduction

The demographic changes related to the increasing numbers of elderly people living alone are leading to a significant change in the social and economic structure [1]. Driven by falling fertility rates and a sustained increase in overall longevity of people resulting of advances in medicine and public health services, many countries; especially in the developed world; are now refreshing themselves for the fact that their fastest-growing demographic is the over 80 years old. Furthermore, the linear trend that life expectancies have followed for over a century is carry on increasing. Elder People (here referred aged 65 years or more), are estimated to attain around 30% of the population in the next 30 years [2]. Those people prefer growing old at home and saving their free lifestyles that often come

generally with high risks. Actually, 61% of accidents occur at homes and 85% of them are due to falls. They have around 10,000 deaths each year. However, obtaining a rapid support after a fall decreases the risk of death by 80% [3]. Therefore, many supportive technologies and systems have been developed to track elderly persons and monitor their activities of daily living in order to allow them to age comfortably at home.

The use of sensing floors in ambient intelligence began in the late 1990's, with projects like the Magic carpet [4] by Paradiso et al., and the Smart floor [5] by Orr and Abowd. Besides, the first approach to fall detection using accelerometer was developed in 1998 by Williams et al. [6]. Some sensing floors are already commercially available today, like the FloorInMotion [7] and the SensFloor [8]. But generally, Most of these

systems have their own limitations and do not ensure 100% precision [9]. The proposed project aims to offer a friendly-user and effective system, without disturbing elders in their daily living lifestyles.

This paper describes a novel approach of automatic fall detection system using ground sensors network. This choice is selected for the advantage of the non-disturbing of elder due to the hiddenness of the sensors. For this propose, a smart apartment consists of (kitchen, bathroom, bedroom and living room), with several smart and connected devices was built within INRIA-Nancy. It was covered with a ground sensors network composed of 104 tiles (60*60 cm). Each tile is equipped with an accelerometer and four force sensors positioned at each corner "Figure 1".
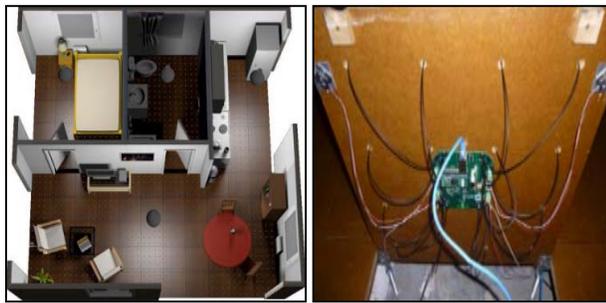

Figure 1. The INRIA-Nancy smart apartment is at the left and the smart tile is at the right.

Each smart tile communicates with its neighbors and any agent laid on it using wireless technology [10]. Consequently, tiles can be exploited to extend mediators' communications and perceptions (of robot or human) [11,12]. A cartography of this apartment composed of smart tiles with their identifiers is showed in "Figure 2".

Figure 2. A cartography of the tiles composing the sensing floor, with their identifiers.

The positions of the sensors are indicated by red points. The walls are shown in black. The tiles under the furniture (sleeping room, toilet, and the kitchen) have been left unequipped with sensors, and are shown in grey color.

2. Materials and Methods

From the signals generated by the accelerometers under the tiles, a set of parameters are extracted to build our database. Furthermore, artificial intelligence techniques

can be profitably of this database to detect elder falls that represents our main objective.

2.1 Data

(1) Synthetic signals: A synthetic database with a Gaussian noise has been generated. It is composed of 200 different observations and 30 parameters that are around a constant value (c) and the value (c±Δ) for the first and second class respectively. "Δ" (delta) is the difference between the two classes representing main two states of this work: falling and non-falling.

(2) Real signals: The sensing floor generates data that can be passed to a data processing software either as a recorded .txt file, or through a ROS publisher/listener interface. The software treats the data packets sent regularly by the tiles every 20 milliseconds. The format of the accelerometer data sent by each tile is as follows:

Information				Accelerometer Data		
Sensor type	Tile ID	msg ID	Timestamp	X	Y	Z
Lsm	18	15786	1.45562E+12	-46	18	-1072

Table 1– Accelerometer data format.

2.2 Methods

The database is fragmented into fall and non-fall fragments to obtain two different classes, and then we proceed to do the windowing of each signal in each class. From each window, we extract some useful parameters and then select the most pertinent of them in order to be used to separate between the two states: falling and non-falling. The accelerometer data processing is shown in "Figure 3".
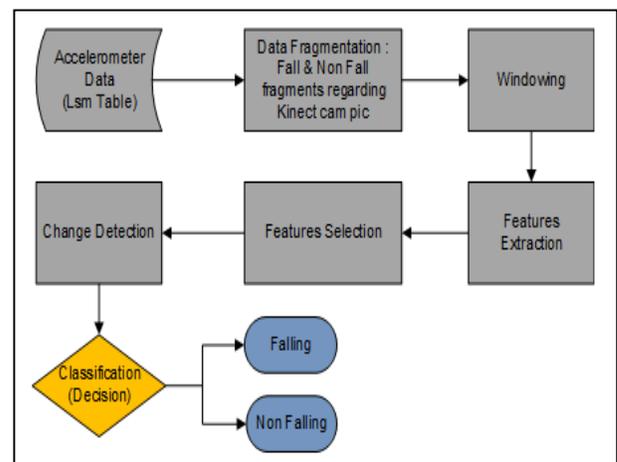

Figure 3. Data processing.

(1) Data fragmentation: For each normal Activity of Daily Living (ADL) and fall actions, the start and the end have been marked based on the videos and the pictures taken from RGB-D cameras.

(2) Windowing: The signal is divided into smaller time slices called windows of fixed length and with a

fixed overlap size with previous and next windows [13]. The size of each window and the overlap have been found through preliminary experiments as 50 samples (sampling frequency = 50) and 25 samples, which correspond to 1 second and 0.5 second respectively.

(3) Feature Extraction: We have extracted all linear and non-linear features from each window. Features have to be carefully selected to get a more descriptive and usually smaller output dataset [14].

a) Linear features

i) Features related to power spectral density: By using the power spectral density (PSD), several variables were calculated such as: mean frequency MPF [15], peak frequency PF [16,17], deciles D1 ··· D9 [12] that contain the median frequency D5 [17,18,19]. Deciles divide the power spectral density into slices holding 10% of total energy.

$$\int_{D_{p-1}}^{D_p} S_x(f)df = 0.1 \int_0^{fmax} S_x(f)df \qquad (1)$$

ii) Parameters extracted from wavelet packet decomposition: The wavelet packet transforms of a signal from the time domain into frequency. Several families exist in wavelets such as Haar, Daubechies, and Symlets which is used in our work. Each window signal is split into an approximation and a detail coefficient that are divided afresh into a second-level approximation coefficients and detail coefficients, and so on [20]. The approximations correspond to smoothed versions of the low-pass filtered signal, and the details contain only the information of high frequencies or discontinuities. Finaly, we calculate the variances on the following details levels 2, 3, 4, 5 and 6 (named W1, W2, W3, W4 and W5) and then used these variances for classification [21].

b) Non-linear parameters

i) Time reversibility: The time reversibility tests if the process dynamics stay well-defined when reversing the time-states' sequence. The TR characteristic of a window signal x is then calculated as following:

$$Tr(\tau) = \frac{1}{N-\tau}\sum_{d=\tau+1}^{N}(x(d) - x(d-\tau))^3 \qquad (2)$$

where N is the length of window signal and τ is the time delay. For more details see [21]).

ii) Lyapunov Exponent: The Lyapunov Exponent (LE) examines the sensibility and the stability on original system states. It measures the trajectory separation rate between adjacent tracks in phase space [22,23]. In this work, we have used the "(3)" to calculate LE described in [22]:

$$\lambda = \lim_{t \to \infty} \lim_{\|\Delta_{d0}\| \to 0} \left(\frac{1}{t}\right) \log(\|\Delta_{dt}\| / \|\Delta_{d0}\|) \qquad (3)$$

where $\|\Delta_{d0}\|$ represents the Euclidean distance between two states of the system to an arbitrary time t_0,

and $\|\Delta_{dt}\|$ corresponds to the Euclidean distance between the two states of the system at a time later t.

iii) Sample Entropy: Sample Entropy (SE) is used to identify the regularity of signals. We have used the Sample Entropy defined in [19] in this work. For a time series x which represents a signal of length N and patterns aj $(0, ..., m-1)$ of length m, with $m < N$, and $aj(i) = x(i+j)$; $(i = 0, ..., m-1; j = 0, ..., N-m)$, the time series x in a time $t = ts, x(ts,..., ts+m-1)$ as a match for a given pattern aj, if $|x(ts+i) - aj(i)| \le r$ $for\ each\ 0 \le i < m$. Sample Entropy is then computed as follows:

$$SE_{m,r}(x) =$$
$$\begin{cases} -\log\left(\frac{C_m}{C_{(m-1)}}\right): C_m \ne 0 \land C_{(m-1)} \ne 0 \\ -\log\left(\frac{N-m}{N-m-1}\right): C_m = 0 \lor C_{(m-1)} = 0 \end{cases} \qquad (4)$$

where N, m, r and Cm represent, respectively, the length of the time series, the length of sequences to be compared, the tolerance for accepting, and the number of pattern matches. "m" is determined by the method of the false nearest neighbors (FNN) and "r" *is* equal to 0.2 according to the collected works [19].

(4) Feature Selection: Aims to find the most relevant features of a classification problem. It is very helpful in improving computational speed and prediction precision. Several feature selection methods have existed in literature (SFS, ReliefF, F-score, etc.), and each one has pros and cons [24]. We introduce and theoretically examine in this paper a new proposed method called **H**istogram **C**omparison **M**ethod **(HCM).**

a) SFS: Is the first method proposed in 1963 by Marill and Green for features selection. SFS starts with an empty data set and proceeds by expanding the data set with the feature, of which addition to the data set boosts the wrapped model performance most. The algorithm adds features in such manner recursively until a stopping criteria is met [25].

b) ReliefF: Aims to estimate the quality of features according to how well their values separate the instances according to their distance in the problem space. For a set of selected instances, the algorithm searches for the k nearest neighbors from the same class and k nearest neighbors from each of the other possible classes. The algorithm updates the feature quality information by accumulative its value if the feature separates instances with different classes well and by reducing its value in the reverse scenario [26].

c) F-score: Offers an effective criterion based on statistic characteristics to measure the discrimination ability of each feature. It is simple and independent of the classifiers. F-score of a feature *(i)* is given by:

$$F(i) = \frac{(\overline{X}_i^{(+)} - \overline{X}_i)^2 + (\overline{X}_i^{(-)} - \overline{X}_i)^2}{\frac{1}{n_+ - 1}\sum_{k=1}^{n_+}(X_{k,i}^{(+)} - \overline{X}_i^{(+)})^2 + \frac{1}{n_- - 1}\sum_{k=1}^{n_-}(X_{k,i}^{(-)} - \overline{X}_i^{(-)})^2} \quad (5)$$

where $\overline{X}_i^{(+)}$, $\overline{X}_i^{(-)}$ and $\overline{X}_i$ are are the averages of the ith feature of the positive, negative and whole datasets. $X_{k,i}^{(+)}$ and $X_{k,i}^{(-)}$ are the ith feature of the kth positive instance and the ith feature of the kth negative instance. Features with higher F-score value are selected [27].

d) HCM: Is a new filter model which calculates the discriminative ability of each feature separately, and it is favorable for two-class classification problems. The HCM algorithm is: An instance is represented by a vector composed of m features values. Starting from the most upper value to the lowest value of the feature with a static threshold. For each step, we count the difference between the numbers of instances belong the two classes that are above the threshold (i.e. $d(P_i)$). After that, we accumulate the different values of $d(P_i)$ denoted Score value. The feature that has the greater Score value is the most relevant for classification. HCM is computed as the follows:

$$S_i = \sum \sum_{thershold}^{+\infty} |N^+ - N^-| \quad (6)$$

where N^+ and N^- are the number of instances that are above the threshold and belong the first and the second class respectively.

(5) Signal change detection: Is the ability to detect that a change occurred on the characteristics of a signal and making some inference about the actual time of change. Most detection algorithms are based on statistical revealing and hypothesis testing [28]. In our application, we developed a simple algorithm to detect the characteristic change of a signal and notice that a person is falling down after he/she was walking, sitting, or standing. The change point identification is the time that a change may have occurred.

3. Results

We started testing our method to select the discriminative parameters on synthetic data and evaluate its efficiency compared to well-known methods in literature. After that we will show the results of parameters extraction and selection and change detection on real data.

3.1 Results on synthetic data

We try to test the efficiency of HCM regarding its efficiency to select relevant features and its computation time. The proposed method shows a good accuracy in relevant features selection. The error rate ratio is around 1% which is clearly lower than ReliefF (30%) and F-score (12%), for (Δ) greater than 0.4. This result is presented in the "Figure 4".
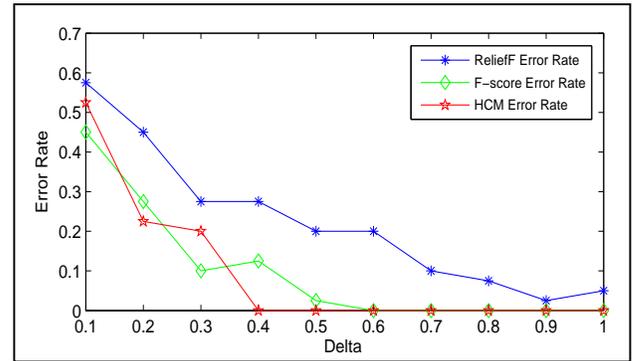

Figure 4. Error Rates Comparison among ReliefF, F-score, and HCM.

In addition, we have been noticed that the computation time of HCM (0.03 s) is less than the ones of ReliefF (0.05 s) and F-score (0.045 s). Therefore, this method can be used in some applications where the time latency is awkward. These results are taken from a machine Intel® Core™ i5-3317U CPU @ 1.70 GHz (4 CPUs), ~ 1.7 GHz with 4 GB RAM.

3.2 Results on real data

The objective of the proposed system is to discriminate between falling and non-falling states using the accelerometer under the tiles. Upon this aim, six persons (one young, four adults, and one elder) were participated to make ten different scenarios repeated five times. These scenarios contain the different activities: walking, sitting, standing, and falling. Activities were made with different ways like soft and hard falls, fast and slow walking, falling from sitting and falling from walking, etc. Our aim is to detect the signal changing when fall occurs on time. It's easy to see the signal change in the "Figure 5". These signals are normalized before being drawn.
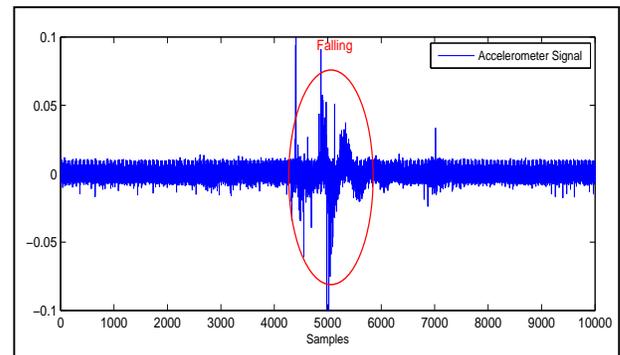

Figure 5: Accelerometer signal

After that, we extract some useful parameters from the original signals that can be used in our system in order to improve the performance regarding the computational speed and the prediction accuracy. "Figure 6" shows some extracted parameters that can be used in the proposed system.
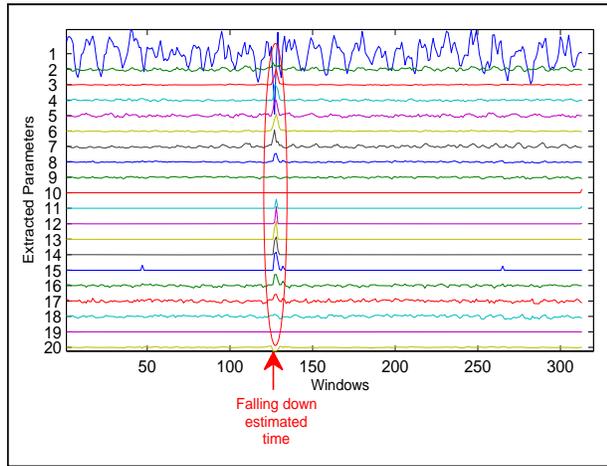
Figure 6. Extracted Parameters (1: TR, 2: DFA, 3-7: Wavelet Packet decomposition parameters, 8: MPF, 9-18 Decil, 19: SE, and 20: LE).

One can see that most of extracted parameters have a peak in case of fall. Therefore, we took one of the most relevant features and then we detect the change in case of fall using a simple detection method. "Figure 7" shows the signal in *(a)*, and the fall detection represented by the changing point identification with a good accuracy in *(b)*.
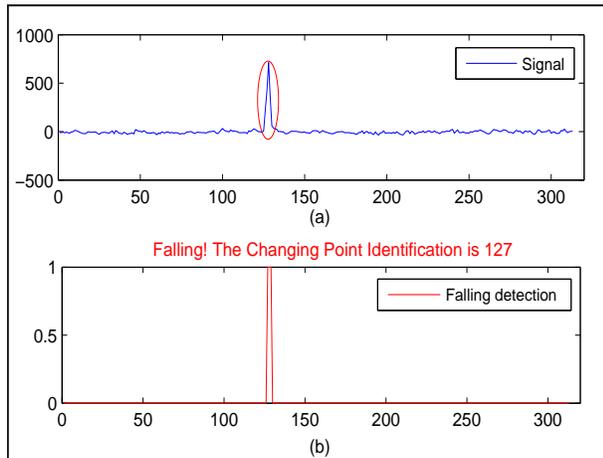

Figure 7: Changing detection of a signal.

Using such parameters instead of the original signals can reduce the dataset size and consequently improve the efficiency of our system.

Several scenarios with different subjects have been realized but only five examples are presented in "Figure 8" due to lack of space.
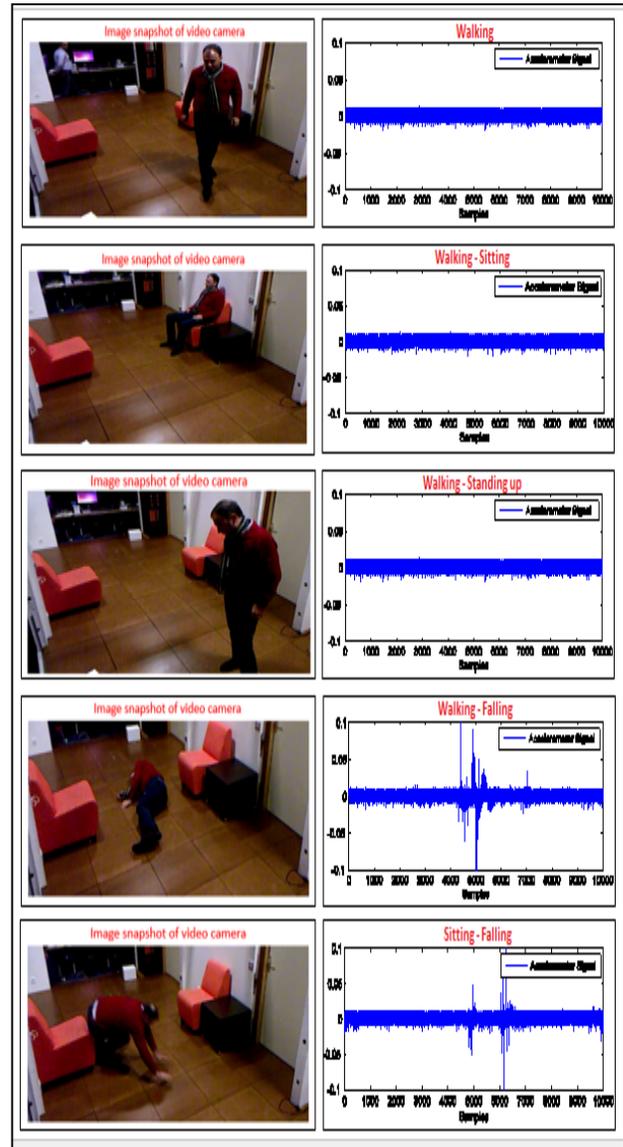

Figure 8: Accelerometer signals' shapes for different postures.

Hence, using only an accelerometer concealed under tiles, the proposed system can easily differentiate between falling and non-falling states "Figure 9". So, we can monitor elder activities and automatically detect the falling cases in their own living apartment.
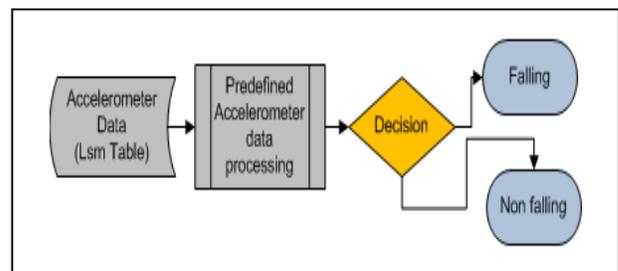

Figure 9. Falling and non-falling decision state.

4. Discussion

Firstly, we presented the aging population problem and the advances in medicine and public health services to monitor the ADL of elders at home in order to support their independency.

Secondly, we used the accelerometer of the INRIA sensing floor to build the dataset used in our system.

Thirdly, we extracted many parameters from accelerometer signals. These parameters are stored in a smaller output dataset that are used in our work in order to increase the efficiency of the proposed system.

Fourthly, we introduced a novel, and efficient algorithm "HCM" to select the most relevant features. Results show a good efficiency in both accuracy and computation time comparing to well-known methods in literature. Then, we apply a signal detection algorithm on the most pertinent feature to detect the signal's changing in case of fall.

Finally, as a perspective, we will try to use the force sensors to locate, track elder, and recognize their activities.

5. Conclusion and future work

This paper described our up-to-date progress on automatic fall detection system using sensing floors. A novel approach was presented that tackle problems such as efficiency, accuracy and usability in fall detection systems.

The next contribution of this work is to fuse the dataset collected from the accelerometers with force sensors data sources to get profit in determine the all ADL states.

Furthermore, merging multi-sensing data with prediction technologies such as artificial intelligence and machine learning will encourage to develop intelligent fall prevention system [29].

Finally, the proposed system has a little high cost especially for the old apartment, but the price of sensors is rapidly decreasing, making it feasible to implement such system. The great challenge of this project is to provide a friendly-user and effective system that doesn't affect elderly daily living patterns.

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