Falls as anomalies? An experimental evaluation using smartphone accelerometer data

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Abstract Life expectancy keeps growing and, among elderly people, accidental falls occur frequently. A system able to promptly detect falls would help in reducing the injuries that a fall could cause. Such a system should meet the needs of the people to which it is designed, so that it is actually used. In particular, the system should be minimally invasive and inexpensive. Thanks to the fact that most of the smartphones embed accelerometers and powerful processing unit, they are good candidates both as data acquisition devices and as platforms to host fall detection systems. For this reason, in the last years several fall detection methods have been experimented on smartphone accelerometer data. Most of them have been tuned with simulated falls because, to date, datasets of real-world falls are not available. This article evaluates the goodness of methods that detect falls as anomalies, thus not requiring to be tuned with fall patterns. To this end, we compared traditional approaches with anomaly detectors by experimenting on three different collections of accelerometer data, and four different data representations. Results demonstrated that in most of the cases, understanding fall patterns is not necessary to design a good and effective fall detection method.

Keywords Fall detection · Anomaly detection · Novelty detection · Accelerometer data · kNN · Smartphone

1 Introduction

Falls are a major health risk that impacts the quality of life of elderly people. When a fall occurs, a prompt notification would help in reducing the injuries that the fall could cause. An effective fall detection system should address the following requirements (Abbate et al, 2012): 1) automatic notification of occurred falls; 2) promptness in order to provide quick help; 3) reliability of the fall detection techniques; 4) communication capabilities, in order to alert the caregivers; 5) usability in order to facilitating users’ acceptance.

Several solutions have been proposed: some of them addressing the problem as a whole, and others focusing on one specific requirement. The contribution of this article is related to the reliability of the fall detection techniques.

Several factors characterize a fall detection technique: from the sensors used to acquire data, to the features extracted; from the algorithms used to detect falls, to the types of datasets used to train the algorithm. The approaches that have been proposed differ for the choices with respect to those factors.

For what concerns data acquisition, ambient sensors, wearable sensors, or a combination of the two, are the principal data sources used in these techniques (Mubashir et al, 2013; Liming Chen et al, 2012). Many recent approaches investigate the possibility of using the sensors provided by smartphones (Medrano et al, 2014; Sposaro and Tyson, 2009; Abbate et al, 2012), which are widespread and require almost no installation or set-up. Moreover, they do not introduce any additional cost, can be used in any place, and are accepted by end users because they are already part of their everyday life.
The techniques also differ in the data type used to detect falls. Most popular fall detection techniques exploit accelerometer data as the main input to discriminate between falls and activities of daily living (ADL). Fig. 1a shows an example of accelerometer data representing a fall that are extracted from the dataset provided by (Medrano et al, 2014). In particular, the fall was recorded with a smartphone Galaxy mini. Fig. 1b illustrates the accelerometer data recorded by two sensors respectively placed on a Galaxy S II (from the dataset by (Anguita et al, 2013)) and a Galaxy Nexus (recorded by ourselves). These data capture the walk performed by two different subjects. It is possible to notice that the captured data share a general trend. This suggests the possibility of defining a method for the detection of falls that can be general and independent from the specific devices.

To verify the effectiveness of the method used by the technique to detect falls, data acquired by the sensors are arranged into labeled datasets containing both ADL and falls, usually simulated by volunteers. Often datasets are elaborated in order to obtain features: from simple raw data to more complex indicator (such as, magnitude and Fourier transform) whose processing requires time and computational resources. Methods can be principally divided into two main categories: domain knowledge- and machine learning techniques-based (Mirchevska et al, 2014). The approaches currently proposed, regardless of their classification, have in common the fact that they require a set of falls in their training phase. Unfortunately, human simulations are significantly different from real-world falls (Klenk et al, 2011), and this could make those fall detection techniques not feasible for real-world applications.

For this reason, Medrano et al (2014) experimented the use of a machine learning techniques based on one-class classifier that has only been trained on ADL to detect falls as anomalies with respect to ADL. In particular, their experimentation was conducted with a k-Nearest Neighbour (kNN) classifier. As data representation they used the magnitude that does not require an huge amount of resources to be calculated.

Medrano et al (2014) experimented on a publicly available dataset containing both ADL and fall patterns simulated by several human subjects and recorded by the same device. Moreover, Medrano et al (2014) also experienced a two-classes Support Vector Machine (SVM) on the same dataset. SVM has produced slightly better results with respect to the one-class kNN. Thus, they concluded that novelty detectors are infeasible in detecting falls. However, SVM and kNN are very different classifiers in terms of efficiency and complexity. Thus, in our opinion, their comparison is inadequate. On the opposite, a comparison between a one-class kNN and a two-classes kNN would have been more representative of the novelty detector performance. Finally, in the article they explicitly state that data are acquired by accelerometers mounted on smartphones. This suggests that it was taken into consideration the idea of running the analyzed methods on smartphones. From our point of view, a smartphone hardly support the execution of a SVM ensuring good performance.

The aim of our work is to evaluate the quality of a one-class classifier tuned with ADL only on a set of features computed from accelerometer data acquired by smartphones. In particular, we have chosen the kNN classifier evaluated on a set of features (raw data, magnitude, accelerometer features, and local temporal patterns) that can easily computed on a smartphone in order to identify the better candidate in detecting falls. We have evaluated the robustness of the one-class kNN method with respect to the variations of acquisition conditions: different sensors, different human subjects, different sensor position. All the experiments have been conducted on two publicly available datasets (Medrano et al, 2014; Anguita et al, 2013). Evaluation metrics, such as area under the curve (AUC), sensitivity and specificity, have confirmed, in most of the cases, that anomaly detection techniques are quite robust against variations of acquisition conditions. Moreover, the results have been compared with a two-classes kNN classifier. In specific configurations, the one-class kNN performed better then the two-classes kNN. For the sake of completeness, we have also experienced a two-classes SVM. In this case, in specific configurations, the one-class kNN and SVM achieved close performance.

The rest of the paper is organized as follows: Section 2 introduces the motivations of our work and discusses related works; Section 3 outlines the experiment design; Section 4 presents the results of the experimentations; Section 5 discusses the achieved results; finally Section 6 provides some details about the future directions.

2 Motivation and Related Work

In the near future the number of older people is expected to grow. Indeed, the World Population Ageing Report states that the global share of elderly people (aged 60 years or over) will reach more than 21% by 2050 (more than 2 billion people) (United Nations, 2013). Ageing results from the demographic transition, a process where reductions in mortality are followed by reductions in fertility (United Nations, 2013; Carone and Costello, 2006). The increasing trend of life expectancy has been directly proportional to the increase in disability (Karmarkar, 2009). Thus, oldest people
Falls as anomalies? 

Fig. 1 Examples of accelerometer data: (a) A walking activity from two different smartphones performed by two different subjects. (b) A fall as acquired by a smartphone.

represent the greatest challenge in providing health-related services and identifying ways to assist them in maintaining independence (Mann, 2004). Indeed, the 31.2% of people aged 80 to 84, and 49.5 percent of those over age 85, require assistance with everyday activities (Federal Interagency Forum on Aging-Related Statistics - National Center for Health Statistics, 2012). This increase results in a growing need for supports (human or technological) that enable the older population to perform daily activities (US Census Bureau, 2013).

Intensive research efforts have been and are still focused on the identification of solutions that from one side automatically assist elderly people in performing daily activities and, on the other side, promptly detect anomalous situations related to diseases or to situations purely related to the old age, such as the worsening of the mild cognitive impairment (Acampora et al, 2013), the prompt identification of conditions favorable to heart failures (Deshmukh and Shilaskar, 2015), and the prompt detection of falls (Mubashir et al, 2013).

Falls are a major health risk that impacts the quality of life of elderly people. Among elderly people, accidental falls occur frequently: the 30% of the over 65 population falls at least once per year; the proportion increases rapidly with age (Tromp et al, 2001). Moreover, fallers who are not able to get up more likely require hospitalization or, even worse, die (Tinetti et al, 1993). Thus, several approaches have been proposed to prompt detect falls. They mainly differ with respect to (i) the sensors used to acquire data, (ii) the data repre-
sentation (features) used by the method, and (iii) the method used to detect falls.

Table 1 summarizes the analysis performed on a set of significative approaches. The table has been specifically designed to highlight the characteristic features of each approach in terms of (i) sensors, (ii) data representation and (iii) methods. In particular, the first two columns show the method and the training set configuration respectively. The third column states whether the approach requires a set of falls to train the algorithm. The fourth column lists the set of features used to infer a fall. Finally, the fifth and sixth columns respectively specify the type of wearable sensor used to sense data (ad hoc solutions or smartphone’s sensors) and the involved sensors.

Table 1 aims at providing an idea of how many different approaches are proposed. Most of the approaches rely on data coming from ad-hoc wearable sensing devices, only a few on smartphone’s sensors. The mainly used sensors are accelerometers. The approaches use features that are very different each other, some of them very complex in terms of computation. Half of the approaches is based on thresholds-based techniques and the other half on machine learning techniques. Finally, most of the approaches are based on methods that require a set of fall to train the underlying algorithm.

Other approaches not outlined in Table 1 can be found in the many surveys dedicated to the fall detection (e.g., Mubashir et al (2013); Mohamed et al (2014); Hijaz et al (2010)). Among the others, Bagal et al (2012) is particularly interesting because it compares the most popular techniques for the identification of falls based on accelerometer data.

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2.1 Sensors and data representation

Fall detection methods rely on data acquired by sensing devices. Images, accelerometer data, audio, angular velocities are only a few examples of data. Data are captured by environmental or wearable sensors or by a combination of both (Mubashir et al, 2013; Liming Chen et al, 2012). Ambient sensors introduce many issues such as privacy, installation costs, and invasiveness. Moreover, a person can fall everywhere. Thus, wearable sensors are more indicated for the specific application domain. Under the umbrella of wearable sensors fall ad-hoc solutions and smartphones’ sensors. Ad-hoc solutions generally include a microcontroller and a set of attached sensors. Such artifacts are then placed in specific area of the body (e.g., wrist, arm, ankle). Thus, they require an explicit acceptance by the elderly people.

On the opposite, smartphones are generally present in everyday life. Therefore, the use of smartphones do not require changes in daily habits and do not involve additional costs.

Despite the type of wearable device, most of the approaches use accelerometers, a few accelerometers with gyroscopes. For this reason, our experimentation has considered accelerometers only.

As regards features, Table 1 shows how the various approaches use features of different nature. Therefore, there not exists a common trend. The unique feature that is found with greater frequency is magnitude.

It is possible to notice that some of the used features are generic such as the magnitude, the energy, and the standard deviation. Others are specifically related to the application domain, such as the time of free fall, the time of reverse impact, and the time of inactivity.

Some of them are performing (such as, magnitude and Fourier transform), but require high processing times and/or considerable computing resources with respect to the application domain and, in case of smartphone, to the device on which the features will be calculated. Indeed, timeliness and lightness in the computation are crucial factors so that those features can be used with effectiveness on smartphones.

2.2 Methods

Methods can be divided into domain knowledge- and machine learning techniques-based (Mirchevska et al, 2014): the former usually apply heuristics, while the latter usually rely on the definition of classifiers able to detect falls. From our perspective, regardless of the type, what differentiates the techniques is the need for data representing falls in the data set used to train the algorithm. Most of the proposed approaches require falls in the training data set in order to properly configure their method. Falls are mostly realized relying on volunteers that are asked to perform daily activities (such as, sitting, walking, and so on) and to simulate falls.

Even if the achieved results by those approaches are very promising, it is quite difficult to generalize the results because almost always the experimentation is limited to one ad-hoc data set only. In addition, as stated by Klenk et al (2011), simulated falls significantly differ from real-world falls. Thus, having simulated falls in the training dataset could lead to realize classifiers that may show different behaviors with real-world falls.

For the above considerations, a method based on the detection of anomalies with respect to ADL may be a better solution for this kind of application domain. Fall detection is not the only case in which the detection of anomalies is the better choice in designing a classifier. There are many other situations in which real-world
Table 1 Related work

| Approach          | Method          | Falls needed? | Features                                                                 | Smartphone Ad-hoc | Sensors                              |
|-------------------|-----------------|---------------|---------------------------------------------------------------------------|-------------------|--------------------------------------|
| Medrano et al (2014) | K-means+NN      | no            | - Magnitude                                                               | Smartphone        | - Triaxial accelerometer            |
| Tolkiehn et al (2011) | Threshold based | yes           | - Magnitude of standard deviation per axis                               | Ad-hoc            | - Triaxial accelerometer            |
|                   |                 |               | - Std of the magnitude                                                   |                   | - Barometric pressure               |
|                   |                 |               | - Ratio of the polar angle                                               |                   |                                      |
|                   |                 |               | - Delta of two consecutive polar angles                                   |                   |                                      |
|                   |                 |               | - Barometric pressure                                                    |                   |                                      |
| Wang et al (2014)  | Threshold based | yes           | - Signal magnitude vector                                                 | Ad-hoc            | - Triaxial accelerometer            |
|                   |                 |               | - Hearth rate value                                                        |                   | - Hearth rate monitor               |
|                   |                 |               | - Trunk angle                                                             |                   |                                      |
| Bourke et al (2007) | Threshold based | yes           | - Magnitude                                                               | Ad-hoc            | - Dual-axis accelerometers placed orthogonally |
| Li et al (2009)    | Threshold based | yes           | - Magnitude of acceleration                                               | Ad-hoc            | - Triaxial accelerometer            |
|                   |                 |               | - Magnitude of angular velocity                                           |                   | - Triaxial gyroscope                |
| Zhang et al (2006) | One-class SVM   | yes           | - Time of free fall                                                        | Ad-hoc            | - Triaxial accelerometer            |
|                   |                 |               | - Variance of acceleration during free fall                               |                   |                                      |
|                   |                 |               | - Time of reverse impact                                                   |                   |                                      |
|                   |                 |               | - Mean and variance of acceleration during reverse impact                 |                   |                                      |
| Chen et al (2006)  | Threshold based | yes           | - Magnitude                                                               | Ad-hoc            | - Dual-axis accelerometers placed orthogonally |
| Nyan et al (2008)  | Threshold based | yes           | - Correlation coefficient between thigh and waist deviation from vertical axis | Ad-hoc            | - Triaxial accelerometer            |
|                   |                 |               | - Correlation coefficient between angular velocity and reference template |                   | - Two-axis gyroscope                |
| Abbate et al (2012) | Threshold based | yes           | - Magnitude                                                               | Smartphone        | - Triaxial accelerometer            |
|                   |                 |               | - Time of inactivity                                                       | Ad-hoc            |                                      |
|                   |                 |               | - Peak time                                                                |                   |                                      |
|                   |                 |               | - Impact start                                                             |                   |                                      |
|                   |                 |               | - Impact end                                                               |                   |                                      |
| Ge and Shuwan (2008) | Threshold based | yes           | - Inertial frame vertical acceleration                                     | Ad-hoc            | - Triaxial accelerometer            |
| Mellone et al (2012) | Threshold based | yes           | - Inertial frame vertical velocity                                         | Smartphone        | - Two-axis gyroscope                |
| Mellone et al (2012) | Threshold based | yes           | - Time of free fall                                                        | Ad-hoc            |                                      |
| Shibuya et al (2015) | SVM             | yes           | - Range of angular velocity                                               | Ad-hoc            | - Triaxial accelerometer            |
| Zhuang et al (2015) | SVM             | yes           | - Range of acceleration                                                    | Ad-hoc            | - Two-axis gyroscope                |
| Sposaro and Tyson (2009) | Threshold based | yes           | - Magnitude                                                               | Smartphone        | - Triaxial accelerometer            |
| Dai et al (2010)   | Threshold based | yes           | - Angle of body                                                            | Smartphone        | - Triaxial accelerometer            |
| Lee and Carlisle (2011) | Threshold based | yes           | - Magnitude                                                               | Smartphone        | - Triaxial accelerometer            |
| Albert et al (2012) | SVM             | yes           | - Moment (mean, abs(mean), std, skew, kurtosis)                           | Smartphone        | - Triaxial accelerometer            |
|                   |                 |               | - Moments of the difference between successive samples                     |                   |                                      |
|                   |                 |               | - Smoothed root mean squares                                               |                   |                                      |
|                   |                 |               | - Extremes (min, max, abs(min), abs(max))                                 | Smartphone        | - Triaxial accelerometer            |
|                   |                 |               | - Histogram                                                                |                   | - Magnetometer                      |
|                   |                 |               | - Fourier components                                                       |                   |                                      |
|                   |                 |               | - Mean magnitude, mean of cross products (xy, xz, yz), abs(mean of cross products) |                   |                                      |
| Fang et al (2012)  | Threshold based | yes           | - Magnitude                                                               | Smartphone        | - Triaxial accelerometer            |
|                   |                 |               | - Vertical acceleration value                                              |                   | - Gyroscope                          |
data are very difficult to achieve: imagine a system able to infer terrorist attacks. Real world training set are very rare or even in-existent. From the related work analysis, only Medrano et al (2014) have assessed the robustness of one-class classifiers trained with a set of ADL. Indeed, Medrano et al (2014) agree with us stating that “traditional approaches to this problem suffer from a high false positive rate, particularly, when the collected sensor data are biased toward normal data while the abnormal events are rare”.

Medrano et al (2014) also experimented a two-classes SVM (Support Vector Machine). They concluded that SVM allows to obtain best results with respect to one-class KNN classifier in detecting anomalies. Although the goodness of the results, a SVM implementation would be too much expensive in terms of computation resources to be a mobile application. From our point of view, a more interesting comparison could have been with a two-classes KNN technique.

3 Experiment Design

In this article we focus on methods that detect falls exploiting smartphone accelerometer data. In particular we evaluated the robustness of such anomaly detectors compared to that of traditional detectors that, in turn, are tuned with fall patterns. To this end we designed several experimental setups by varying both materials and methods:

- **Data**: we have created three different collections of smartphone accelerometer data by mixing the data of two publicly available smartphone accelerometer data (Medrano et al (2014) and Anguita et al (2013)) that have been recorded by different devices with different setups. We have created two sets of these collections selecting different sizes of time window of the accelerometer patterns. Experimenting on these collections permits to assess the robustness with respect to changes in acquisition conditions.

- **Feature vectors**: we experimented four different feature vectors ranging from the most simple to the most complex ones: raw data, magnitude, accelerometer features, local temporal patterns. Assessing the goodness of feature vectors is very meaningful especially in a mobile and real time environment where the computational capacity may be limited.

- **Classification schema**: we compared 2 different classification schemas based on the k-Nearest Neighbour (kNN) classifier: one-class (corresponding to the anomaly detector) versus two-classes. Finally, a brief comparison, for sake of completeness, has been carried out with a two-classes Support Vector Machines (SVM). This comparison is very crucial because it lets to determine if falls can be reliably detected as anomalies.

3.1 Publicly available datasets

One of the considered datasets contains both Activity of Daily Living (ADL) and falls performed by ten participants, 7 males and 3 females, ranging from 20 to 42 years old (Medrano et al, 2014). The ADL set has been recorded during real-life conditions: participants carried a smartphone in their pocket for at least one week to record everyday behaviour. On average, about 800 ADL records were collected from each subject during this period. Participants simulated eight different types of falls: forward falls, backward falls, left and right-lateral falls, syncope, sitting on empty chair, falls using compensation strategies to prevent the impact and falls with contact to an obstacle before hitting the ground. Participants wore a smartphone in both their two pockets (left and right) and performed the falls on a soft mattress in a laboratory environment. They repeated each fall three times for a total of 24 fall simulations. The dataset contains 503 falls and 7816 ADL.

The accelerometer pattern has been recorded through the built-in triaxial accelerometer of a Samsung Galaxy Mini phone running the Android operating system version 2.2. The sampling rate was not stable, with a value of about 45 ± 12 Hz. During the daily life monitoring, whenever a peak in the acceleration magnitude was detected to be higher than 1.5 g (g = gravity acceleration), a new pattern was recorded. Each entry included information in a time window of 6 s around the peak. During each fall simulation, a 6 s width time window around the highest peak. Afterwards, the offset error of each axis was removed and an interpolation was performed to get a sample every 2 ms (50 Hz). We will refer to this set of data as dataset1.

The other dataset considered contains only ADL performed by a group of 30 volunteers with ages ranging from 19 to 48 years (Anguita et al, 2013). Each person was instructed to follow a protocol of 6 activities: standing, sitting, laying down, walking, walking downstairs and upstairs. Each subject performed the protocol twice while wearing a Samsung Galaxy S II smartphone: on the first trial the smartphone was fixed on the left side of the belt and on the second it was placed by the user himself as preferred. The tasks were

\footnote{The authors declared that due to technical issues some falls had to be repeated in a few cases, so the number is higher than 24 \times 2 \times 10}
performed in laboratory conditions but volunteers were asked to perform freely the sequence of activities for a more naturalistic dataset. The accelerometer signals were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 s and 50% overlap, thus obtaining 128 readings/window. The total number of accelerometer patterns is 10299. We will refer to this set of data as dataset2.

For the analysis presented in this paper, we considered two different sub-windows of the accelerometer patterns taken around the peak. More in details, we considered two sub-windows of:

- 2.56 s corresponding to a vector 128 samples;
- 1 s corresponding to a vector of 51 values.

3.2 Data Collections description

As discussed before, we have created three different collections of smartphone accelerometer data by mixing the data of two publicly available smartphone accelerometer data (Medrano et al (2014) and Anguita et al (2013)). For the evaluation we used a 10-fold cross-validation approach. The three data collections are then composed of 10 folds, each containing 90% of training data and 10% of test data. More in details:

- Collection 1. ADL: 7035 training and 781 test data. FALL: 453 training and 50 test data. Both ADL and FALL data have been taken from the dataset1;
- Collection 2. ADL: 7035 training and 781 test data. Half of ADL data have been randomly taken from the dataset1 and half from the dataset2; FALL: 453 training data and 50 test data. All the FALL data have been extracted from the dataset1;
- Collection 3: ADL: 9270 training data and 1029 test data. All the ADL data have been taken from the dataset2; 453 FALL training data and 50 FALL test data. All the FALL data have been extracted from the dataset1.

3.3 Feature vectors

As discussed before we considered four different feature vectors extracted from two different size of data patterns: 2.56 s corresponding to a vector 128 samples and 1 s corresponding to a vector of 51 values. More in details we considered:

Raw data. This is the simplest representation. Each pattern is composed of the concatenation of the three accelerometer data \((x, y, z)\), one for each direction. We obtain a final feature vector of size 384 for the case of 128 samples and 153 for the case of 51 samples.

Magnitude. This vector of features has been obtained from the three accelerometer data \((x, y, z)\) as follows:

\[
M = \sqrt{x^2 + y^2 + z^2}.
\]

We obtained a vector of size 128 and another of size 51.

Accelerometer features. These feature vectors have been obtained by concatenating four different features for each direction: mean of the acceleration pattern, standard deviation of the acceleration pattern, energy of the acceleration and correlation of the acceleration. The dimension of the final feature vector is of size 12.

The energy of the acceleration is calculated as follows:

\[
\text{Energy} = \sqrt{\frac{\sum_{i=1}^{N} |a_{\text{fft}}|^2}{N}},
\]

where \(N\) is the number of samples of the pattern and \(a_{\text{fft}}\) are the fast Fourier transform components of the input pattern. The correlation of the acceleration is calculated between couple of directions: \(x\) versus \(y\), \(x\) versus \(z\), etc.

Local Temporal Patterns. This feature is the most complex representation. The feature vector is composed of the concatenation of patterns achieved by comparing the magnitude of each sample \((M_i)\) with the several boosted magnitude values of \(N\) neighbor samples \((M_j)\). The boosted magnitude values corresponding to a given neighbor \(i\) are achieved by increasing the original magnitude by an increasing decimal factor:

\[
M_i^n = n + M_i,
\]

with \(n\) ranging from 0 to \(M_{\text{max}}\). The value \(M_{\text{max}}\) corresponds to the nearest decimal value of maximum magnitude. For each sample we have \(M_{\text{max}}+1\) comparisons as results of the following inequality:

\[
M_s > M_i^n.
\]

The result of each comparison is represented as a binary vector map of size \(N\) with 1 indicating if the above inequality is satisfied and 0 if not. All the comparison maps are then summed in order to obtain a single vector map of size \(N\). The number of neighbors has been set to \(N = 6\). The final feature vector is obtained by concatenating all the maps achieved for each sample thus obtaining \(6 \times 51 = 306\) and \(6 \times 128 = 768\).

3.4 Methods and their evaluation

We have considered the one-class k-Nearest Neighbour (kNN) classifier as novelty detection technique. This classifier has been trained only with ADL patterns and tested with both ADL and FALL patterns. Given a
test pattern, if the novelty score is higher than a given threshold, the new record is classified as a novelty/fall otherwise is classified as an ADL. By varying the threshold, the receiver operating characteristic curve (ROC) and the area under the ROC curve (AUC) can be obtained. We calculated also a specific value of sensitivity \( SE = \frac{True\ Positives}{Positives} \) and specificity \( SP = \frac{True\ Negatives}{Negatives} \). These values have been obtained by selecting the point that maximized their geometric mean \( \sqrt{SE\cdot SP} \), in a ROC curve averaged over the cross-validation results.

We compared the novelty detector with a two-classes kNN. This classifier has been trained and tested with both ADL and FALL patterns. We converted the distances achieved by the kNN into scores ranging from 0 to 1. By thresholding the scores we draw the ROC curve. Finally, a global comparison has been made with a binary radial basis SVM trained with both ADL and FALL patterns.

All the algorithms have been implemented in Matlab and tested with a PC equipped with Ubuntu 14.10 distribution. Regarding the two variants of kNN we used \( k = 1 \) and the Euclidean distance as the distance measure. Regarding the SVM classifier, we used the built-in Matlab package. This package allows to find automatically the regularization and kernel parameters \(^2\), and to achieve scores as outputs along with decisions. By thresholding these scores we obtain the corresponding ROC curve.

In order to make the results reproducible, the data collections as well as the Matlab code used for the experiments is available on the authors’ website \(^3\).

### 4 Results

In table 2 we report the results achieved on the three collections by all the classification schemas and feature vectors in the case of accelerometer patterns made of 51 samples. In this case, the one-class kNN and two-classes kNN and SVM achieve close performance in every cases. It should be noticed that the performance achieved in the case of the 51 samples by all the kNN based solutions are 10% better than the case of 128 samples. Moreover, even in this case the raw data demonstrated to work better than more complex feature vectors.

The results achieved by the SVM classifier in the case of 128 samples make clear that the two-classes classifier performs better than a novelty detector. This is not so true in the case of 51 samples where we demonstrated that using raw data the gap between SVM and the novelty detector is very small. This results overcome the results achieved by Medrano et al (2014). They demonstrated that a two-classes SVM is much better than a novelty detector when the accelerometer data is represented as magnitude and is composed of 51 samples.

In Fig. 2 we represents the ROC curves corresponding to the results achieved on three collections by the novelty detector with raw data as feature vector. It is visible from the figures that raw data representation is quite robust to the number of samples and that achieve high performance on all the collections.

### 5 Discussion and conclusion

In this work we evaluated the robustness of anomaly detectors (one-class classifier) compared to that of traditional two-classes detection methods that, in turn, are tuned with fall patterns. To this end, we experimented several methods on three different collections of accelerometer data, and four different feature vectors. The experiments have demonstrated that:
a very simple feature vector based on raw data is very robust to detect falls in both one or two classes schemas;

– a greater number of samples of the accelerometer pattern penalizes kNN classification schemas. In contrast, the SVM classifier does not seem to suffer from changes in the number of samples;

– in the case of 128 samples a novelty detector is reliable only if it is based on raw data. In the case of 51 samples a novelty detector is reliable if it is based on both raw data and magnitude in the case of 51 samples;

– new accelerometer data are required to better evaluate the robustness of the methods;

Overall, considering that in the case of raw data, the gap between the SVM and one class kNN is very small, we can conclude that a fall detection system based on a novelty detector is feasible in a real context. This is especially true considering the limited computation capacity of the smartphone. In fact, the raw data does not require further processing and the kNN schema is based on a simple Euclidean distance.

6 Future directions

In order to further validate the robustness of our approach, we should be able to experiment with additional datasets. These datasets should contain ADL performed by different people and recorded by different smartphones.

As the number of data sets freely available is extremely reduced, we decided to develop an application that is able to acquire data from smartphones’ sensors and to automatically label them (falls or ADL). This enables us to enrich the datasets of ADL and of simulated falls.

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Table 2 Results obtained by both k-NN schemas on the three collections. Here the accelerometer patterns contain 128 samples.

| C. Feat. | Class. | AUC | SE | SP | √SE·SP |
|----------|--------|-----|----|----|--------|
| RAW 1-c  | 0.952  | 0.914 | 0.909 | 0.907 |
| 2-c      | 0.989  | 0.974 | 0.973 | 0.973 |
| svm      | 0.984  | 0.976 | 0.986 | 0.981 |
| 1-c      | 0.816  | 0.824 | 0.701 | 0.760 |
| svm      | 0.876  | 0.586 | 0.714 | 0.782 |
| Magn.    | 0.976  | 0.904 | 0.971 | 0.937 |
| 1-c      | 0.810  | 0.814 | 0.697 | 0.753 |
| svm      | 0.855  | 0.812 | 0.718 | 0.763 |
| Energ.   | 0.888  | 0.972 | 0.957 | 0.965 |
| 1-c      | 0.818  | 0.894 | 0.642 | 0.758 |
| svm      | 0.839  | 0.872 | 0.673 | 0.766 |
| LTP      | 0.977  | 0.948 | 0.938 | 0.943 |

Table 3 Results obtained by both k-NN schemas on the three collections. Here the accelerometer patterns contain 51 samples.

| C. Feat. | Class. | AUC | SE | SP | √SE·SP |
|----------|--------|-----|----|----|--------|
| RAW 1-c  | 0.980  | 0.962 | 0.939 | 0.950 |
| 2-c      | 0.986  | 0.950 | 0.974 | 0.962 |
| svm      | 0.956  | 0.902 | 0.914 | 0.908 |
| Magn. 1-c | 0.961  | 0.906 | 0.916 | 0.911 |
| svm      | 0.975  | 0.922 | 0.951 | 0.937 |
| 1-c      | 0.810  | 0.814 | 0.697 | 0.753 |
| svm      | 0.989  | 0.974 | 0.959 | 0.966 |
| Energ. 1-c | 0.938  | 0.914 | 0.896 | 0.905 |
| svm      | 0.984  | 0.962 | 0.923 | 0.942 |
| LTP 2-c  | 0.990  | 0.966 | 0.959 | 0.963 |
| svm      | 0.988  | 0.958 | 0.986 | 0.972 |

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