ACCELEROMETER DATA PREPARATION FOR ACTIVITY RECOGNITION

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ABSTRACT

This paper presents an approach to activity recognition using wearable accelerometers. The focus of this paper is on the process of data preparation which is of great importance for the activity recognition. The data preparation starts with the low and high pass filters which are applied on the raw data. Then, 25 attributes are computed for each accelerometer. Machine learning algorithm − Random Forest is used for evaluation. Results achieved with one, two and three accelerometers are presented. The results showed that with appropriate data preparation techniques small number (i.e. one or two) of accelerometers is sufficient for achieving acceptable performance (F-measure above 93%).

1 INTRODUCTION

There are a lot of projects and useful applications aiming at nursing older people. Most of them belong to the area of ambient intelligence and are trying to make an everyday life easier, simpler and safer for elderly. The research presented in this paper is a part of the Confidence project [1], which aims to create a remote care system to detect health problems of the elderly by monitoring their posture and activities. In this paper we present our work on the activity recognition using wearable 3-axis accelerometers.

After analyzing the related studies in terms of data preparation techniques, we noticed that usually researchers do not analyze or quickly go through the data from the accelerometers. Usually they are more focused on the algorithms. On contrary, in this research we were more interested in understanding the accelerometer's data and implementation of data preparation techniques.

In activity recognition process we analyzed seven target activities*: standing, sitting, lying, sitting on the ground, on all fours, going down,* and *standing up*. We also investigated the performance with different numbers of accelerometers (1 to 3). This way we showed the improvement of the system as the number of accelerometers is increased. The final system should be as non-intrusive as possible (fewer wearable accelerometers), but still accurate enough to detect each activity.

The classification algorithm used for the research is Random Forest [2]. This was the algorithm yielding the best results after analyzing several classification algorithms. For the experiments 11 young people were recorded performing the same scenario 5 times each. The leave-one-person-out (i.e. cross validation with 11 folds) technique was used for evaluation.

2 RELATED WORK

Activity recognition is an exciting area for the development of robust techniques, as applications in this field typically require to deal with high-dimensional, multimodal streams of data that are characterised by a large variability (e.g. due to changes in the user's behaviour or as a result of noise). However, unlike other applications, there is a lack of established benchmarking problems and datasets. Typically, each research group tests and reports the performance of their algorithms on their own datasets using experimental setups specially conceived for that specific purpose. For this reason, it is difficult to compare the performance of different methods.

Most of the researchers investigate the activity recognition problem **using machine learning techniques.**

Of particular interest are the results presented in [3]. A mobile phone was used as an accelerometer. The target activities differ from ours. Only three out of eight were common. The process of attribute computation consists only of the computation of statistical attributes (mean, variance, etc.). When they used the same person's data for training and testing the achieved accuracy was 90%, but when they used a different person's data for testing the accuracy drops to 65%. In our research we use data from different people for training and testing.

A similar evaluation approach to ours is used in [4]. The leave-one-person-out cross-validation evaluation technique is performed. They used the data from six people data for training and one person's data for testing. They used a Neuro-Fuzzy classifier and one accelerometer fixed on the wrist. In the process of attribute computation standard statistical attributes were computed, but also an analysis in the frequency domain was performed. Unfortunately, we had only two out of eight activities in common. The reported overall accuracy is 93%.

In [5] the authors collected data from three users using two accelerometers to recognise five activities, i.e. walking, sitting, standing, running, and lying down. This paper claimed that data from a thigh accelerometer was insufficient for classifying activities such as sitting, lying down, walking, and running, and thus multiple accelerometers were necessary (a claim that is also proved with our research). They achieved an accuracy of 62% for the ankle accelerometer, 83% for the thigh and 95% for both accelerometers.

3 ACCELEROMETER

A **3-axis accelerometer** is a sensor that returns a real-valued estimate of the acceleration along the axes *x*, *y* and *z*. It measures the acceleration and output the projections of the acceleration vector represented in a 3D coordinate system. In Figure 1 an accelerometer with its coordinate system is presented. Because of the Earth's gravity, all objects experience a gravitational pull towards the Earth's centre. When the accelerometer is at rest, the only force that is affecting the sensor is the Earth's gravity. The acceleration unit of the pull is referred to as *g* or *g*-force. Consequently all objects are subject to 1 *g* acceleration. Figure 2 shows the accelerometer with its coordinate system and the *g*-force that is influencing it. This information about the *g*-force is of great interest to us. Using the gravity component we can find out the orientation of the sensor (e.g. vertical, horizontal), which enables us to distinguish between different activities (e.g. standing, lying).

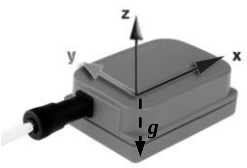

Figure 1: *Sensor-specific 3D coordinate systems.*

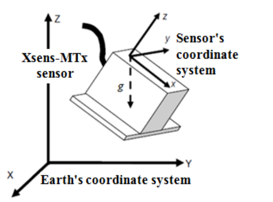

Figure 2: *Earth and sensor specific 3D coordinate systems.*

The measured acceleration vector is directed upwards (positive value for the *z* axis), even though the gravitational force pulls downwards. That means that only when the accelerometer is in free fall it will measure a value of zero. Even though its speed is increasing, it is in an inertial frame of reference, in which it is weightless. When the accelerometer is at rest, it will measure 1 *g* upwards. The accelerometer is not measuring gravity, but the force of the surface on the body that counteracts gravity.

4 DATA PREPARATION

4.1 Filters

Because the data is received from sensors (which usually means noisy data), additional filtering techniques were applied. There are several techniques that perform signal filtering. In our research we applied a **low-pass** and **high-pass** filter [6].

A simple **low-pass filter** for data in time domain is a smoothing function. In other words, the filtered signal is smoother and less dependent on short changes.

For the activity recognition task one of the most important features is the orientation (inclination) of the accelerometer. Therefore we had to use techniques that will filter out the portion of the acceleration data caused by gravity from the portion of the data that is caused by motion of the accelerometer. To do this, we used a low-pass filter to reduce the influence of sudden changes on the accelerometer data. The resulting filtered values then reflect the more constant effects of gravity. Actually with the low-pass filter we isolated the gravity component from the acceleration data.

It is also possible to filter a series such that the low-frequency variations are reduced and the high-frequency variations are unaffected. This type of filter is called a **high-pass filter**. This is especially important in the acceleration data, in which this filter allows us to eliminate the gravity component and take into consideration only the isolated sudden changes in acceleration.

Algorithm 1 shows the version of the low-pass and high-pass filters that we use in our research. It uses a low-value filtering factor to generate a value that uses 20% of the unfiltered acceleration data and 80% of the previously filtered value. This factor was chosen empirically.

Algorithm 1: *Low-Pass and High-Pass Filter.*

```
alpha = 0.8
Filter BEGIN
        Low_X = alpha × Prev_X + (1 − alpha) × Curr_X
        Low_Y = alpha × Prev_Y + (1 − alpha) × Curr_Y
        Low_Z = alpha × Prev_Z + (1 − alpha) × Curr_Z
        High_X = Curr_X − Low_X
        High_Y = Curr_Y − Low_Y
        High_Z = Curr_Z − Low_Z
Filter END
```

As shown with the sample code above, the low and high passed acceleration values are stored in *Low* and *High* 3D vectors respectively. The previous acceleration values are stored in the *Prev* 3D vector and the current values are stored in the *Curr* 3D vector.

4.2 Attribute Computation

This subsection describes the process of computing the attributes. These attributes are later combined to create the final attribute vector which is used in the machine learning − classification stage. All the attributes are computed by using the technique of **overlapping sliding windows**.

Sliding window is a common approach to solving the problem activity recognition. Usually the algorithms do not try to recognise each data sample that is received from the sensors, but are trying to recognise some pattern in the data that is over some time interval (window).

In time series analysis, a sliding window is a technique that combines set of data samples in one window. A window

size is the time interval for which the data is collected. If the widows have some data samples as intersection, then this technique is named overlapping sliding windows.
Because the final sampling frequency of our accelerometers was 6 Hz, we chose a window size of six, which is one-second time interval. We decided for one-second time interval because in our target activities there are transitional activities (standing up and going down) that usually last from one to four seconds.

Length of the Acceleration Vector

The first computed attribute is the length of the acceleration vector. It is a simple but very useful attribute, which is also used further in the process of the computation of new attributes. It is not used as separate attribute in the final attribute vector because of the sliding window technique.

Statistical Attributes

The first sets of attributes that are used in the final attribute vector are the statistical attributes. They are computed for the low-passed filtered values of each of the axes and for the length of the acceleration vector. Three statistical features are computed: *Mean Value, Root Mean Square* and *Standard Deviation*.

Accelerometer Movement Detection

When a person's body is static, the accelerometer responds only to the gravity, producing a constant 1 *g* total acceleration. During motion the accelerometer produces a changing acceleration signal and the fiercer the motion, the greater the change in the signal. Using these changes in the acceleration vector, an attribute is computed for the detection of the accelerometer movement: *Acceleration Vector Changes (AVC)*. The AVC value of this attribute increases as the accelerometer is in motion (walking, going down, standing up, etc.). This attribute takes into consideration the data from the current window (six data samples). It sums up the last six differences of lengths of the acceleration vector and divides the sum by the time interval (one second) of the data. The AVC is computed as follows:

$$AVC = \frac{\sum_{i=1}^{n} | length_i - length_{i-1} |}{T_n - T_0} \quad (1)$$

T_0 is the time stamp for the first data sample in the window, and T_n is the time stamp of the last data sample. With this attribute the movement of the person can be detected: it distinguishes static from dynamic activities. For this attribute the raw value for the length of the acceleration vector is used instead of the low-passed value. The reason for this is that we are more interested in the small changes in the acceleration signal and the low-pass filter smoothes these changes.

Max-Min Value

An additional attribute that is computed is the difference between the maximum and the minimum value of the acceleration vector in the current data window. The difference between these two values is bigger in transitional activities (e.g. going down, standing up).

Accelerometer Inclination Angles

With accelerometer inclination angles we conclude the attribute computation subsection. The most important characteristic for activity recognition is the inclination (i.e. orientation, tilt) of the accelerometers. Accelerometer's data is used to measure the static angle of inclination. The inclination angles are calculated as the angles between the actual acceleration (e.g. the Earth's gravity for static activities) and each of the axes (Figure 3).

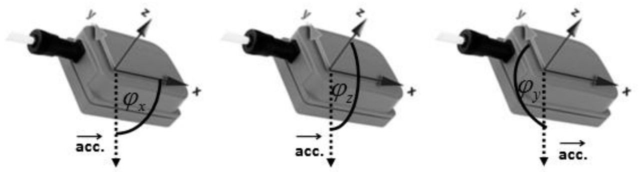

Figure 3: *Accelerometer inclination angles.*

For instance, the angle φ_x between the acceleration vector and the x axis is computed as follows:

$$\varphi_x = \arccos\left(\frac{a_x}{\sqrt{a_x^2 + a_y^2 + a_z^2}}\right), \quad (2)$$

where the values a_x, a_y and a_z represent the actual acceleration vector.
It should be noted that for the computation of these angles, low-passed filtered data is used, because it has fewer changes and the angle has fewer variations. Without the low pass filter the angles were sensitive to each small change of the accelerometer. These angles improve the classification of activities that have different accelerometer angle inclinations. For instance, when the chest accelerometer is in vertical position the user is probably standing or sitting. The horizontal position of the accelerometer indicates that the person is lying or is on all fours. The sitting on the ground activity is user dependent and in most of the cases is in between these two groups. Similarly the accelerometer placed on the thigh can distinguish between standing and sitting, but has problems distinguishing between sitting and lying. Different body placements of the accelerometers can give different information about the target activities.

5 ACTIVITY RECOGNITION

After the step of data preprocessing and computation of all additional attributes, the final attribute vector is created. This attribute vector is passed to the classification model which tries to recognise (classify) the appropriate activity of the user. This process is shown in Figure 4. Because the main focus of this research is the data preparation process, the next steps are briefly described.
Machine learning approach was used for the activity recognition. In this study, the machine learning task is to learn a model that will be able to classify the target activities (e.g. standing, sitting, etc.) of the person wearing accelerometers. The classification step was performed using

the application program interface of the software toolkit WEKA (Waikato Environment for Knowledge Analysis) [7]. Random Forest [2] was the algorithm that yielded the best results. It is an ensemble method for decision trees.

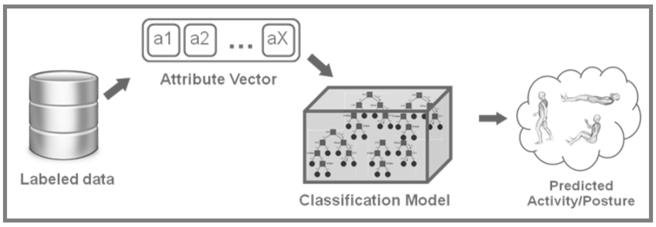

Figure 4*: Activity Recognition Flow Chart*

5.1 Classification Results

The experimental dataset was recorded by 11 people (7 males and 4 females). Special test scenario was created, which included all target activities. The test scenario was performed 5 times by each person. The events in the scenario were recorded in a single recording. The tests were conducted in an experimental laboratory. The total number of instances without the overlapping sliding window technique was **316 314**. After implementing the sliding window technique, the final amount of instances was reduced to **105 438.**

The leave-one-person-out cross-validation technique was used for evaluation. Thus, each fold was represented by the data of one person. This means the model was trained on the data recorded for ten people and tested on the remaining person's data. This procedure was repeated for each person data (11 times) and the average performance was measured.

The F-measure evaluation metric was used as the most suitable for our research. The results are shown in Figure 5. The F-measure for each activity is presented. The body placements of the accelerometers were chosen to be: the chest, the thigh and the ankle.

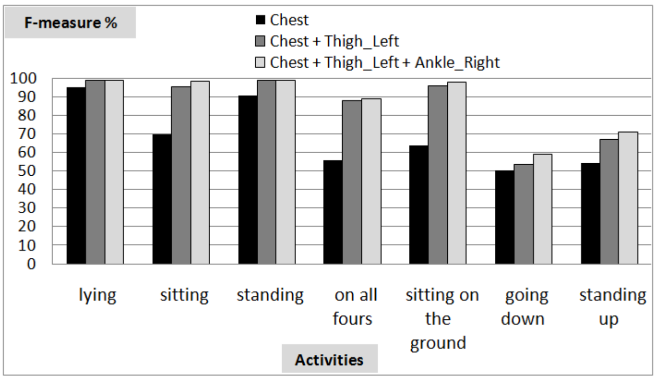

Figure 5: *Results achieved for each activity.*

The overall F-measure was 93% when the system was using one accelerometer; 96.4% and 98% with two and three accelerometers respectively. The results show that there is obvious improvement in the system when the number of accelerometers increases from one to two. When the third accelerometer is added to the system, the improvements are minimal (by 1.5 percentage point overall).

6 CONCLUSION

Data preparation is challenging task in machine learning. It is especially important step in activity recognition systems that rely on sensor data. In our research we used wearable sensors (i.e. accelerometers); therefore, the data is noisy and requires additional preprocessing techniques.

The first step towards the final solution was the step of understanding the raw data. After this, filtering techniques were applied.

Second step was the attribute computation step. Finding the appropriate attributes that will describe the user's behaviour was of particular interest. The behaviour needs to be represented by simple and general attributes, so that the algorithm using these attributes will also be general and work well on behaviours different from those in our scenario.

The final step in our research was the evaluation using machine learning algorithms. The results showed that with appropriate data preparation techniques small number of accelerometers is sufficient for achieving overall F-measure above 93%.

ACKNOWLEDGMENTS

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