Accelerometer signal pre-processing influence on human activity recognition

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ACCELEROMETER SIGNAL PRE-PROCESSING INFLUENCE ON HUMAN ACTIVITY RECOGNITION

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Abstract: *A study of data pre-processing influence on accelerometer-based human activity recognition algorithms is presented. The frequency band used to filter-out the accelerometer signals and the number of accelerometers involved were considered in terms of their influence on the recognition accuracy*.

1 Introduction

Human activity recognition (AR) plays an important role in many of the R&D projects concerning Quality of Life or eHealth [1-3]. Not only the amount of movements but also precise information about the movement type are crucial in nowadays context-aware computer applications. For example recognizing particular activities, such as walking or hands positioning, enables disease symptoms recognition and analysis for Parkinson' disease patients [4, 5].

Most popular techniques for AR utilize accelerometer data [6-8]. Modern 3-axis accelerometers, being small and light electronic devices [6], allow capturing movement characteristics for different body positions [6-8]. The resulting data can be processed by different classifiers in order to recognize various activities of analyzed subjects. The literature provides an exhaustive description of classification techniques used for that purpose [7-9]. However, most of the authors pay little or no attention to the pre-processing of the accelerometer data. Meanwhile, few available studies on this subjects [10] clearly indicate the importance of careful selection of the pre-processing techniques in this context.

Pre-processing of the accelerometer data includes: filtering, selection of time frame and hop lengths, choosing the number of features as well as the number of accelerometers necessary for successful classification. This paper presents the study of filtering and number of accelerometers influence on the AR accuracy.

In the next section a data acquisition protocol is introduced. It describes how the data used in experiments were obtained. Third section presents two classifiers used in our study. Those were the Neural Networks (NN) and the k-nearest neighbours algorithm (k-NN). In the fourth section experiments are given. They include simulations involving different filtering bands and simulations with various number of accelerometers. Experiments are followed by conclusions.

2 Data acquisition

It was necessary to capture body acceleration data for the presented study. The Shimmer platform was used for this task [11]. Each Shimmer sensor comprises: microprocessor, Bluetooth radio, 3-axis accelerometer and MicroSD card. Shimmers allow preparing dedicated firmware for specific purposes. This approach enables creating own data collection platforms (either by writing own firmware or by modifying available OpenSources).

Accelerometers positioning used for the data collection was based on some similar studies available in the literature [12]. Two sensors were placed on the left and on the right wrists, another two on left and on right ankles, and one sensor on the chest. Fig.1 depicts sensor positioning as well as their axis polarization.

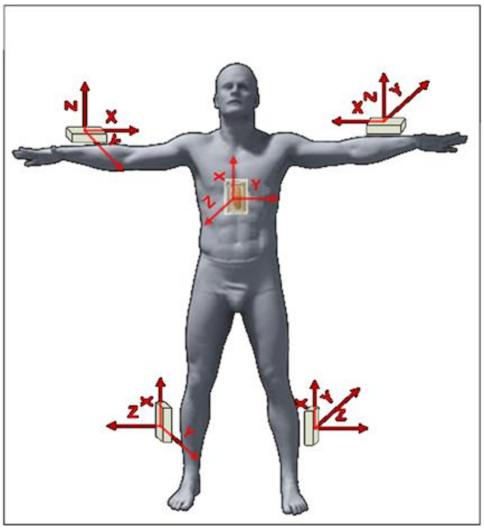

Fig. 1. Accelerometers positioning and their axis polarization

All recorded activities were performed by young, healthy and right-handed subjects. Average age in the subjects group was 25 years with the standard deviation equalling 2.8 years. Activities were performed by 16 people (2 women and 14 men). Recordings were made in laboratory conditions, with the subjects supervised, according to a predefined list of activities.

Data were recorded on a microSD card. The sampling frequency of the sensors was set to 51.2 Hz and the range of the allowable acceleration was set to ± 4 g (where g is the gravity acceleration equalling 9.80665 m/s^2). Both values allow recording of typical human body activities.

All accelerometers were synchronized with an external PC clock. Additional video recordings were made during the acceleration data acquisition in order to capture the information as to how the subjects performed specific activities.

The predefined list of activities included:

- sitting down on a chair, sitting on a chair, standing up from a chair;
- lying down on a bed, lying on a bed, standing up from a bed;
- walking, climbing stairs, running, standing;
- picking an object with one hand, and with two hands.

Activities were repeated three times by each subject. During the recordings one person produced 20 minutes of acceleration data. The entire recording session produced more than 320 minutes of acceleration data, which corresponds to 44 MB of storage data (assuming 12 bit resolution).

3 Classifiers description

Two distinctive, every-day like activities were chosen for this study. These are: *Walking* – being a representative of dynamic activity, and variety of *Hand positioning* – representing a typical static activities. All other activities listed above were used in the training phase as counter examples, i.e. representatives of categories *No walking* and *None* for hand positioning.

Features necessary to classify different activities were calculated for overlapping time frames. Frame and hop sizes were chosen according to the literature [10]: 8 Sa hop size and 64 and 32 Sa frames size for walking and hands position recognition, respectively.

Features calculated for each time frame consist of time- and spectrum-based characteristics.

3.1 Time-domain features

Mean value (1) – the parameter representing the total level of the acceleration in the analyzed data frame. Its value is higher for dynamic activities (e.g. walking) and smaller for static activities (e.g. hand positioning):

$$\bar{a} = \frac{1}{N}\sum_{n=1}^{N} a(n) \tag{1}$$

where n is sample number in the acceleration data and N represents time frame length.

Standard deviation – depicts the signals variation range:

$$std = \sqrt{\left(\frac{1}{N-1}\sum_{n=1}^{N}\left(a(n)-\bar{a}\right)^2\right)} \tag{2}$$

The kurtosis was calculated to determine the dynamics of acceleration signal:

$$krt = \frac{m_4}{std^2} - 3 \tag{3}$$

where m_4 is the 4th central moment.

The crest factor, i.e. max to RMS value, shows signal impulsiveness:

$$cf = \frac{\max(a(n))}{\sqrt{\frac{1}{N}\sum_{n=1}^{N} a(n)^2}} \tag{4}$$

A relation between different limbs movement can be represented by the correlation coefficients, calculated using acceleration signals recorded for limbs. In the presented study the correlation between corresponding axes of all 5 accelerometers were calculated, e.g. right leg X axis vs. left hand X axis (30 combinations in total).

Correlation allows to capture temporary limp positions as well. Thus in this study the correlations coefficients were calculated also between X, Y and Z axes of a particular accelerometer (15 combinations in total).

The following formula was used to calculate correlation coefficients:

$$corr(a_i^l, a_j^m) = \frac{\overline{a_i^l a_j^m} - \overline{a_i^l}\,\overline{a_j^m}}{std(a_i^l)std(a_j^m)} \tag{5}$$

where i = 1..5 and j= 1..5 represent accelerometer numbers whereas $l=\{x, y, z\}$ and $m=\{x, y, z\}$ accelerometer axes. Correlation between different limbs were calculated for $i \neq j$ and $l=m$. Correlation between particular accelerometer axes for $i=j$ and $l \neq m$.

3.2 Frequency-domain features

Movement complexity is depicted by the acceleration energy:

$$Eng = \frac{\sum_{k=1}^{K} A(k)^2}{K} \tag{6}$$

where $A(k)$ is the k-th spectral line of the acceleration signal's amplitude spectrum and K is the total number of lines. In the described experiments K=64 DFT was used.

The movement periodicity can be judged from the acceleration signal entropy:

$$Ent = -\sum_{k=1}^{K} p(k)\log_2\left(p(k)\right) \quad (7)$$

where $p(k)$ represents the probability of occurrence of A(k) value in the amplitude spectrum. Small entropy values indicate signal periodicity.

Due to the number of axes (i.e. 3 for each accelerometer), the number of accelerometers (5) and the number of features, the overall feature vector consist of 135 values (i.e. 15 means, 15 standard deviations, 15 kurtosis, 15 crests factors, 45 correlation coefficients, 15 energies and 15 entropies).

3.3 NN classifier

As resulted from experiments, it was necessary to design two NN classifiers: one for walking and the second one for hands position recognition. Both of them had the same number of inputs (135), but a different number of hidden layers and output neurons. In both cases activation functions of hidden layers were set to sigmoid functions and for the output layer to linear functions [13].

The first classifier – used for walking recognition – had a simpler structure. It is because the *Walk* and *No Walk* classes are well-separable. The designed NN architecture had one hidden layer with 66 neurons and output layer with two neurons (V shape).

The second classifier had a more complex architecture with two hidden layers. The first hidden layer had 66 neurons, whereas the second had 33 neurons. The output layer consists of four neurons (V shape).

In both NNs the output neurons corresponded to recognized activities. The error back propagation training algorithm was used. The same training and testing procedures were employed for both NN classifiers. Subsequently, the leave-out-out testing procedure was used.

3.4 k-NN classifier

The k-NN classifier is a representative of the ‘lazy classifiers’ group, which requires a large set of training examples to give satisfying results [14]. This classifier calculates the distances between the tested example and all data vectors in the training set. Then it chooses k results which are closest to the tested example according to some predefined metrics. The Euclidean distance was chosen as the metric, defined as follows:

$$d_{euk}(e,t) = \sqrt{\sum_{f=1}^{135}(e_f - t_f)^2} \quad (8)$$

where: e represents the investigated case, t is an example from the training set, f indicates feature number.

In this study, k value was set to 3, because as it was found empirically, it brings the most accurate classification results. The activity appearing most frequently in the k nearest neighbour algorithm was selected as the final classification result.

For the k-NN classifier it is essential that features used for the classification are normalized. Otherwise features with greater values are more influential on the classification results. Furthermore, it is crucial to use only those parameters ensuring a good separation of analyzed activities.

4 Experiments

This section presents experiments investigating influence of the accelerometer signals pre-processing on the AR accuracy. The pre-processing routines included: signal filtering and adjusting number of accelerometers. The classification accuracy was assessed according to the assumption that specificity is more important than sensitivity. This means that the proportion of negatives which were correctly identified, i.e. *No Walk* examples recognized correctly, was decisive during the classifiers comparison.

4.1 Filtering

Filtering of acceleration signals may improve AR accuracy. Especially the low-pass filtering (LPF), which removes redundant information connected to involuntary human movements (e.g. tremor), allows for a better classification. In this study two different LPF cut-off frequency (f_{cut}) values were examined: 6 Hz corresponding to the typical frequency range covering most human activities [7]; and 3 Hz representing the lowest frequency of a typical tremor [1, 4]. An additional filtering was applied in the range of <0.5, 3 Hz> for recognizing of walking. That was because of the fact, that the typical gait is depicted by frequencies starting from 0.6 Hz [7]. An additional scenario – involving only lowest frequencies – was studied for hand positions recognition. It was included in order to examine the classification accuracy using only the DC component (a technique frequently postulated in the literature [7-9]). Classification results (i.e. confusion matrixes) obtained for different activities with various filtering bands are given in Tabs 1 to 4.

Table 1. NN walking AR results for different f_{cut} values

f_{cut}	0-6 Hz		0-3 Hz		0.5-3 Hz	
Act.	*Walk*	*No*	*Walk*	*No*	*Walk*	*No*
Walk	**99.55**	0.45	**99.80**	0.20	**98.79**	1.21
No	0.01	**99.99**	0.04	**99.96**	0.17	**99.83**

Table 2. k-NN walking AR results for different f_{cut} values

f_{cut}	0-6 Hz		0-3 Hz		0.5-3 Hz	
Act.	*Walk*	*No*	*Walk*	*No*	*Walk*	*No*
Walk	**99.64**	0.36	**99.64**	0.36	**60.60**	39.40
No	1.42	**98.58**	1.39	**98.61**	9.66	**90.34**

The first table presents recognition results for the NN classifier. The second table shows similar study results involving the k-NN classifier. In both cases the highest accuracy (in terms of both sensitivity and specificity) was achieved for the acceleration signals low-pass filtered with the f_{cut}=3 Hz and 6 Hz. This indicates that the information stored in the frequencies above 3 Hz does not play an important role in recognizing of walking. A significant accuracy decrease for the k-NN classifier with the filtering band <0.5, 3 Hz>, not reflected in the NN results, indicates that the DC component can play an important role for some classifiers.

Table 3. NN hands position AR results for different f_{cut} values

f_{cut}	Act.	*Left*	*Right*	*Both*	*None*
0-6 Hz	*Left*	**99.55**	0.00	0.00	0.45
	Right	0.00	**95.55**	1.52	2.92
	Both	0.48	6.67	**84.35**	8.51
	None	0.01	0.28	0.64	**99.07**
0-3 Hz	*Left*	**99.31**	0.00	0.00	0.69
	Right	0.00	**97.17**	0.00	2.83
	Both	6.98	0.90	**81.35**	10.76
	None	0.24	0.21	0.64	**98.91**
0-0.5 Hz	*Left*	**96.63**	0.28	0.20	2.89
	Right	0.00	**93.02**	0.57	6.41
	Both	1.72	6.41	**83.43**	8.44
	None	0.18	1.14	0.51	**98.17**

Table 4. k-NN hands position AR results for different f_{cut} values

f_{cut}	Act.	*Left*	*Right*	*Both*	*None*
0-6 Hz	*Left*	**84.12**	0.16	1.14	14.59
	Right	0.63	**76.63**	1.80	20.94
	Both	2.58	3.15	**66.44**	27.83
	None	0.07	0.11	0.47	**99.35**
0-3 Hz	*Left*	**62.26**	0.52	2.78	34.45
	Right	1.07	**54.08**	3.14	41.72
	Both	4.70	2.98	**55.37**	36.95
	None	0.34	0.16	0.77	**98.74**
0-0.5 Hz	*Left*	**32.48**	2.13	4.76	60.63
	Right	4.64	**25.56**	3.75	66.05
	Both	3.92	2.67	**24.41**	69.00
	None	2.12	1.58	2.57	**93.74**

Tabs 3 and 4 present the accuracy of hands position AR. A different LPF brings comparable results for the NN classifier. This indicates, that for NNs the most relevant information is stored in the DC components.

The k-NN classifier is more pre-processing dependent. Here accuracy decreases substantially with the f_{cut}. It may be that small accuracies are caused by the frequency-based features (i.e. entropy, energy, kurtosis). After filtering-out the higher frequencies, those features decrease separation efficiency of sets representing the *Left*, *Right*, *Both* and *None* categories. This is because the values of frequency-based features are similar for all of those categories.

4.2 Number of accelerometers

As it looks from the results given in section 4.1 it follows that the NN classifier gives better AR scores than the k-NN classifier. Therefore, only the NN was chosen to study the influence of accelerometers number on the classification accuracy.

Tab. 5 depicts the walking AR accuracy dependence on the accelerometers number. The 3 Hz LPF was used prior to the accelerometers number reduction, because it allows for most accurate walking recognition (see section 4.1). The following combinations of accelerometers were examined during the study:

- 5 – including signals from all sensors (see Fig. 1),
- 3 – removing signals from sensors placed on wrists,
- 2 – removing signals from sensors placed on wrists and on a chest.

The NN classifier ensured higher accuracies for the *No walk* category regardless of the number of accelerometers. *Walk* classification was more dependent on the number of accelerometers. Nonetheless, even when their number was reduced to two, accuracy was still higher than 99%. This indicates that using only two accelerometers should be sufficient for a successful walking recognition.

Table 5. NN walking AR results involving different number of accelerometers

Acc. No	5		3		2	
Act.	*Walk*	*No*	*Walk*	*No*	*Walk*	*No*
Walk	**99.80**	0.20	**99.56**	0.44	**99.27**	0.73
No	0.04	**99.96**	0.06	**99.94**	0.07	**99.93**

A similar experiment was performed for the NN hand positions classifier. Acceleration signals were LPF with the f_{cut}=0.5 Hz. However, sensors number reduction was different:

- 5 – including signals from all sensors (see Fig. 1),
- 3 – removing signals from sensors placed on ankles,
- 2 – removing signals from sensors placed on ankles and on a chest.

Results obtained for the hands position classification are presented in Tab. 6. It can be seen from the table that the highest overall accuracy was achieved when the number of sensors was reduced to three. As for the signals recorded on ankles, they did not introduce any useful information. In all three accelerometer configurations, lowest accuracies were achieved for the *Both* hand position category. It remains uncertain, as to whether that was caused by the involuntary hands movements occurring for the *None* category (this category was most frequently confused with others).

Table 6. NN hands position AR results involving different number of accelerometers

Acc. No	Act.	*Left*	*Right*	*Both*	*None*
5	*Left*	**96.63**	0.28	0.20	2.89
	Right	0.00	**93.02**	0.57	6.41
	Both	1.72	6.41	**83.43**	8.44
	None	0.18	1.14	0.51	**98.17**
3	*Left*	**98.80**	0.09	0.00	1.11
	Right	0.00	**95.76**	0.47	3.77
	Both	0.00	5.04	**84.38**	10.57
	None	0.04	0.37	0.60	**98.99**
2	*Left*	**98.65**	0.00	0.00	1.35
	Right	0.00	**96.30**	0.00	3.70
	Both	0.57	5.73	**74.99**	18.71
	None	0.32	0.76	0.85	**98.08**

5 Conclusions

The results presented in this paper (mostly in sections 4.1 and 4.2) show that pre-processing of the acceleration signal influences the AR. Both the filtering band and the number of accelerometers should be adjusted prior to the data processing, because some of them may not introduce any beneficial information. Moreover, the redundancies can reduce the AR accuracy.

The presented experiments proved that even 2 accelerometers are enough to classify walking with accuracy higher than 99%, whereas 3 accelerometers are sufficient for recognizing hand positions.

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