THE EFFECT OF WINDOW LENGTH ON THE CLASSIFICATION OF DYNAMIC ACTIVITIES THROUGH A SINGLE ACCELEROMETER

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ABSTRACT
This paper investigates how different window sizes for feature extraction and classification affect the accuracy of daily living locomotors activity recognition through accelerometers. A comprehensive data set was collected from 9 healthy subjects performing walk, stair descending and stair ascending while carrying an accelerometer on the waist. Nearest neighbor based classification has been used because of its simplicity and flexibility. The findings show that, by increasing window length, the system accuracy increases, but it produces delays in real time detection/alert of the activity. From the experiments it is concluded that a 2 seconds (2 s) time window may represent a trade-off for the detection of these mentioned activities in a real-time scenario, as it produces 91.7 percent of accuracy.

KEY WORDS
Inertial sensors, acceleration data, classification, physical activity monitoring.

1. Introduction

Insufficient physical activity appears in around one third of adult population, and more than three million fatalities per year can be associated with this problem. There is a direct connection between physical inactivity and common health problems, including osteoporosis, cardiovascular disease and diabetes [1]. Over the past years, different sensing devices have been used to monitor and automatically quantify the amount and the kind of physical activity [2], and the most popular among them are the inertial sensors incorporating accelerometers and gyroscopes, as they are low cost, small in size and easy to carry. With specific reference to the problem of activity recognition, there is a relevant body of literature investigating the use of accelerometers in fall detection [3-6] and a number of works are related to recognizing different daily activities, like walking, stair ascending, stair descending, sitting, standing, laying and running [7-13] and some activities related to upper limb [14].

In a number of studies, automatic activity recognition is usually performed through multiple accelerometers attached at different locations of the body [6,9,15-20]. Though recognition is higher in this case, carrying multiple sensors on the body may not be advisable if easiness of use is pursued [8].

The studies in which only one accelerometer is used have pointed out the waist location as the best location for activity detection [10,15,21,22,23], but there is a variation in the accuracy results, among different activities. With regard to the discussion about feature extraction, some of the studies used frequency-based features by applying Fast Fourier Transform [24,25], wavelet coefficients [1,20,26], signal magnitude area (SMA) [3,24] and statistical features, including mean, entropy, standard deviation, correlation and skewness [7,8,15,19,20,22]. Different methods and algorithms have been evaluated for the classification of activities, starting from some simple heuristic classifiers [3,16,23,24] to automatic machine learning methods including decision tree, Bayesian networks and K-nearest neighbors (KNN) [7,16,18,21], neural networks [17,22], support vector machines [7,20,23,27] and Markov chains [17,28].

Apart from activity recognition, some of the researchers investigate that the accelerometers can also be used for calculating energy expenditure while performing daily living activities [29]. Its connection with activity recognition is shown by the evidence that regression of energy expenditure through accelerometer data may be different based on the kind of activity that is being performed.

An interesting and still not totally solved problem in activity recognition is deciding the optimal window length to be used for the extraction of features and subsequent classification: in the case of steady state activities higher window lengths for the features extraction are generally used [7,15,29]: this usually increases accuracy in steady state activities, but introduces an increased uncertainty when transitions are taken into account. As an example, by using windows of 10 s [15,29], 6.7 s [16], 5 s [7] with 50 percent overlap and 3.2 s without overlap [8], the shorter activities, such as the transitions between sit and stance, might be skipped out because each transition takes around 1 s to 2 s; some dynamic activities with short durations (such as 2 or 3 walking steps done in the landing platforms between stairs) may be object of misclassification. In real time conditions, these short duration activities account for a non-negligible amount of time. A window size of 2 s was motivated by some researchers as a possible trade-off in this sense, [26,30], but it would be useful for the research to determine if there is an optimal window length for activity classification, provided that this may depend on the goal to be pursued (e.g. for alerting or for energy expenditure estimation).

An open problem, thus, is to determine which is the behavior, in terms of accuracy of a classification scheme, when different window lengths are used. This contribution goes into this specific direction. The rest of the paper is thus organized as follows: the description of the data collection and method is done in section II, results and discussion are given in section III and the conclusions are drawn in section IV.

2. Materials and Methods

2.1 Data Collection

Experiments were performed by using a wireless inertial unit incorporating, among others, a tri-axial accelerometer (ADXL 345) attached to the waist of the subjects with axes along anterior posterior, vertical and medio-lateral directions. Data were transmitted to the system through Bluetooth connection with a sampling rate of 100 samples/s (range of the sensor ± 4g). These specifications were deemed sufficient for getting daily living activity data from waist worn sensor. Figure 1 show the sensor and its placement used during experimentations.

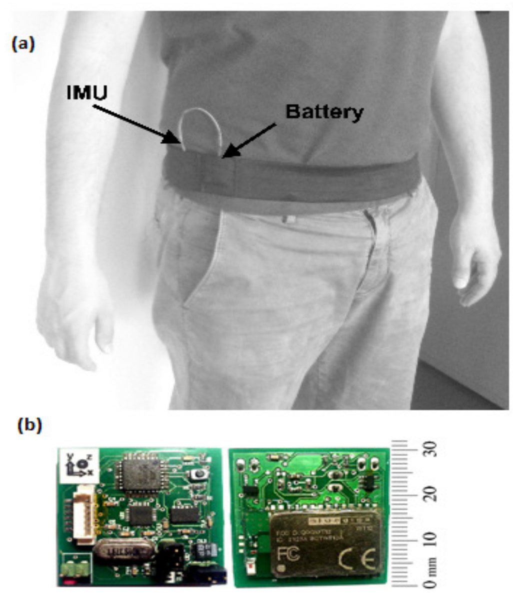

Figure 1. (a) Sensor location. (b) Front and Back view of sensor (ADXL 345) 30*x*30*x*15mm (L×W×H)

Nine healthy younger adults (5 females and 4 males) were recruited for the experimentation, and were asked to walk along a path (~15 meters) with 3 turns of 90 degrees, and go down and up by stairs (48 steps with landing platforms on 12th, 24th and 36th step). Each subject was pre-informed about the activities and path by giving a written note.

2.2 Feature Extraction

Raw acceleration data were preprocessed by applying fifth order, Butter-worth low-pass filter with a cutoff frequency of 18 Hz and labeled according to the performed activities. Features were extracted by passing 2, 3, 4, 5 and 6 s of window over acceleration data with 50 percent of overlap between consecutive windows, as the use of 50 percent overlap is shown effective in previous works [1,16]. Different window sizes were used to check which window size is optimal in terms of real time detection of activities and accuracy. A total of 22 features were computed from each window and their description is given in the list below:

- Mean (x, y and z) and average mean
- Skewness (x, y and z) and average skewness
- Standard deviation (x, y and z) and average standard deviation
- Kurtosis (x, y and z) and average kurtosis
- Correlation (x_y, x_z, y_z, x_total, y_total and z_total).

These features are considered useful in the activity recognition problem [7,16]. The first four feature groups are standard statistical features, while correlation has been considered to improve the activity detection, when activities involve movement of multiple body parts [31]. It is also considered helpful for differentiating among activities that involve translation in just one dimension [7]. Correlation is the ratio between the covariance and the product of the standard deviation between each pair of axes, as shown in the equation below:

$$corr_{(x,y)} = \frac{\operatorname{cov}(x,y)}{\sigma_x \sigma_y}$$

Where cov(x,y) is the covariance between x and y axis and $\sigma_x\sigma_y$ is the product of the standard deviations. All these features were then passed to the classifier for the classification of the activities.

2.3 Classification

For the activity recognition problem, the algorithm should be able to classify among activities efficiently and effectively. So a Nearest Neighbor (NN) classifier was used in this work, as it is considered as a simple and flexible classifier [1]. Parameters of the classifier were tuned to achieve an overall high recognition rate, regardless of the size; euclidean distance metric was used to compute distance between samples and only 1 nearest neighbor was considered to assign the class to the test sample. 10-fold cross validation is pointed out as an effective resampling technique [15,23]. With 10-fold cross validation, classifier is trained with 9 subsets of data and tested with 1 subset until all subsets are used in testing. All experiments were performed in MATLAB environment.

3. Results

Three performance measures (overall accuracy, sensitivity, specificity) were used to organize the results. Figure 2 shows the classification accuracy on the different sizes of windows length on three activity recognition problems.

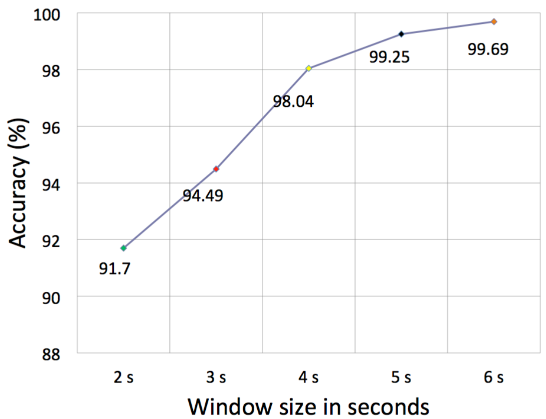

Figure 2. Classification accuracy (%) for different windows sizes

It is clear that in steady state activities the window size and accuracy are proportional: increasing window size means having more information of activity and this may lead to higher recognition rate, but in term of real time detection/alert it may cause delay.

Table 1

Confusion matrix for each window length

Activities	Confusion matrix		
Actual / Predict	**Stair Descend**	**Stair Ascend**	**Walk**
	2 seconds		
Stair descend	**276**	8	32
Stair ascend	9	**307**	20
Walk	11	8	**389**
	3 seconds		
Stair descend	**192**	1	15
Stair ascend	7	**203**	8
Walk	4	3	**257**
	4 seconds		
Stair descend	**146**	0	5
Stair ascend	1	**157**	3
Walk	1	0	**197**
	5 seconds		
Stair descend	**116**	1	1
Stair ascend	1	**125**	0
Walk	1	0	**156**
	6 seconds		
Stair descend	**93**	0	1
Stair ascend	0	**98**	0
Walk	0	0	**128**

Table 2

Performance measure sensitivity and specificity

Performance measure	Window length	Activities		
		Walk	**Stair Descend**	**Stair Ascend**
Sensitivity	**2 s**	95.34	87.34	91.36
Specificity		88.2	93.24	95.04
Sensitivity	**3 s**	97.34	92.3	93.11
Specificity		91.78	94.58	98.06
Sensitivity	**4 s**	100	98.93	100
Specificity		99.22	100	100

Confusion matrix results (Table 1) show that on 2 s window there are number of stair descending and stair ascending records misclassified as walking activity, and this decreases the overall accuracy. Looking at where these misclassifications occurred, most of them resulted those walking steps which were taken on stairs landing steps (12th, 24th and 36th step of stairs) as shown in Figure 3. And by increasing the window size these walking steps were gradually ignored. In time window of 6 seconds, if there is one step of walk (1~1.5 s) on landing step and the remaining interval corresponds to stair descending (4.5~5 s) then this window would more likely represents the stair descending activity and ignores the little change in the activity. So by using smaller size window it may be more likely that sudden changes in activity are correctly classified; at the same time, given a shorter duration, the overall accuracy may decrease. Table 2 shows the sensitivity and specificity measures of each activity along 2, 3 and 6 s windows.

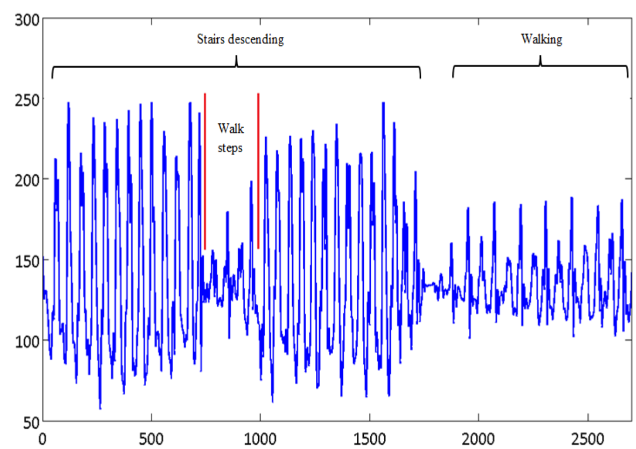

Figure 3. A sample signal of stairs descending where walking activity performed on landing step

Additionally, the number of records that are object of classification depends on the window size. With higher window size the number of records will decrease, thus causing delay in real time detection. Figure 4 shows how the number of steps taken by the participants decreases by increasing the window length with respect to the actual steps. With windows larger than 3 s, a relevant fall in terms of observations occurs.

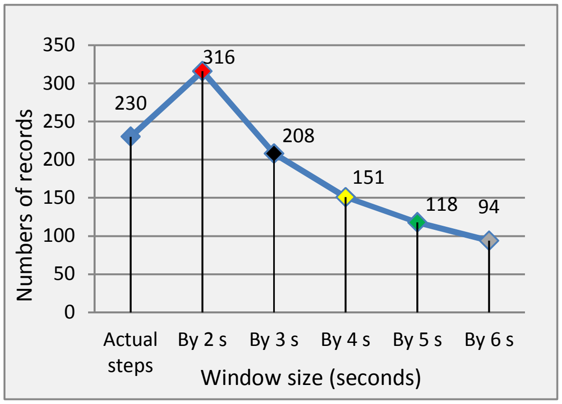

Figure 4. Comparison of stairs descending records extracted by time windows and the actual steps

4. Conclusion

The main aim of this work is to find the best window size for feature extraction in order to get timely and accurate detection of the activity. For real time detection it is necessary to have small delays and to achieve this goal, window size is key. Larger window size (e.g. 10 s with 50 percent overlap) means, for instance, getting one step from 5 s and normally a person can take multiple activities during this time range: as a consequence, a delay occurs in real time detection. In the previous studies it was found that larger window sizes [8,15,29] produce higher accuracy, but may hinder the fall in accuracy associated with the presence of these conditions in real life environments. Experimental results show that 2 s window responds well in real time detection/alert as it is detecting the sudden walking steps in stair landing. The accuracy of the system with 2 s window is 91.71 percent that could be increased up to ~94 percent by including the correctly classified walking steps performed during stairs landings. So, if the optimal window size for classification accuracy depends on the kind of activities that are being performed (such as the number of transitions, and the amount of short duration activities), it is possible that an adaptive method, able to adjust the size of the window based on some information coming from data may be advisable.

Future work is: to increase the number of participants to get a larger data set for evaluation, possibly including elderly people, to check whether there are differences in terms of accuracy results; to add some short interval activities like sit-stands or some sudden transitions to check for window length effect. And, finally, develop a technique able to adapt the window size over time, to maximize classification accuracy.

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