ACCELEROMETER SIGNALS ANALISYS USING SVM AND DECISION TREE IN DAILY ACTIVITY IDENTIFICATION

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Abstract—**the purpose of this work is to implement methods that perform events classification of user activity based on accelerometer signals using two machine learning techniques (Support Vector Machines and Decision Trees). The events of interest are sitting down, standing up, walking and being steady.**

I. INTRODUCTION

The method of activity identification is intended to be used in real time by a small low power microprocessor, thus we will study the viability of options that require less processing power and memory like a decision tree.
The application of these methods will enable continuous recording of daily activity by a wearable sensor by using real time activity labeling instead of simple acceleration logging, the real time processing enables a possible interaction with the user while offline methods do not do.

II. METHODOLOGY

A. Accelerometer device

The experimental data provides from a inertial measuring unit, based on of two orthogonally mounted biaxial differential capacitor MEMS accelerometers ADXL203, this analogical sensor has a measuring range of +/-1,7G and the bandwidth is controlled by two output capacitors, the low pass cut-off frequency -3dB is set at 100Hz to reduce the noise of the signal.

The accelerometers are mounted on a printed circuit board that holds a DSPic, a radio communications module and all necessary components to read and send the data; the sampling rate of the DSPic ADC is 50Hz and the data is sent to a PC using ZigBee, a wireless protocol.

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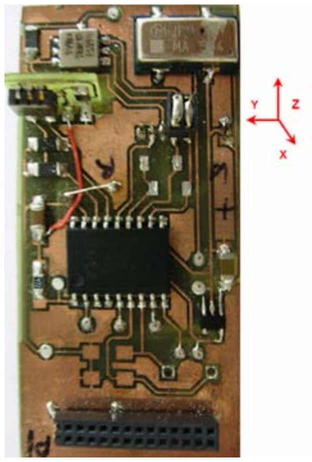

Fig. 1 sensor device DSPic board

The device dimensions are 56x26x18mm, excluding the battery, with the battery that is a set of 4xAAA batteries the weight of the device is about 40g, the device is mounted on an elastic pulsometer band for ease of use. During the exercises the IMU is located on the trunk, above the sternum bone.

B. Experimental procedure

The exercise performed by the test subjects is to stay steady in vertical position then walk about XX meters sit down on a chair stay a few seconds sit, then stand up, walk again and finally sitting down again and finally staying steady again. Each test subject repeats the exercise 3 times, the experiment is video recorded to enable the labeling of activity.

The test group consists on 6 healthy subjects with no mobility limitations:

- Man 59 years old
- Man 30 years old
- Woman 42 years old
- Man 38 years old
- Woman 23 years old
- Man 38 years old

The accelerometer data is labeled by one evaluator using the video feed, labeling 5 possible states: 1 walk, 2 steady,3 standing up, 4 sitting down, 5 steady while sitting, the last one is alike the steady state while standing up so finally we only work on the 4 activity states. This recorded data is used in training the classifier and the evaluation of its performance.

III. TRAINING GROUPS

The labeled helps to identify the action in the acceleration signals but to identify when these action is performed requires a criteria to select similar training signals between the different subjects and number of experiments (3 experiments each 6 subjects). The classifier will be trained using a window of time; the size of the window is studied to achieve the best performance.

$$\theta = \arctan 2(X, \sqrt{Y^2 + Z^2}) \qquad (1)$$

The center of the window used as an input of the stand up and sit down classifiers are the local minimum of the θ signal(1), the rotation of the device around the Y axis. In Fig. 2 there is the center of the window of a sit action a stand up action and another stand up.

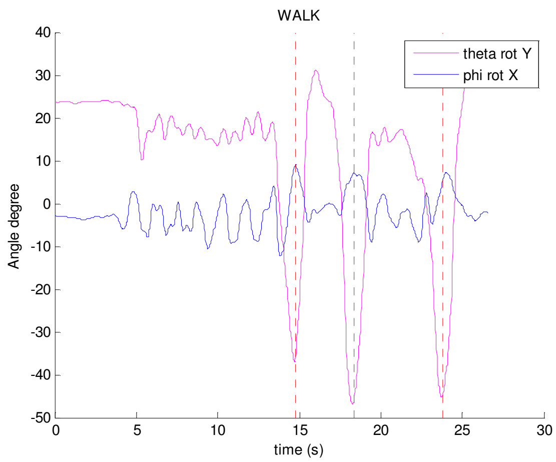

Fig. 2 Theta and Phi angle of node during experiment

A. Stand Up action

The action of standing up from a sit state takes between 1-3.5 seconds (100-175 samples), and it has different phases [1][2] forward bending, active raising ,passive raising and downward bending, the timing and magnitude between these phases determine many pathologic characteristics, besides this work is focused in identifying the action on healthy subjects and the main problem is to differentiate between stand up and sit down. Fig. 2 shows 18 actions of standing up and its 3 acceleration signals.

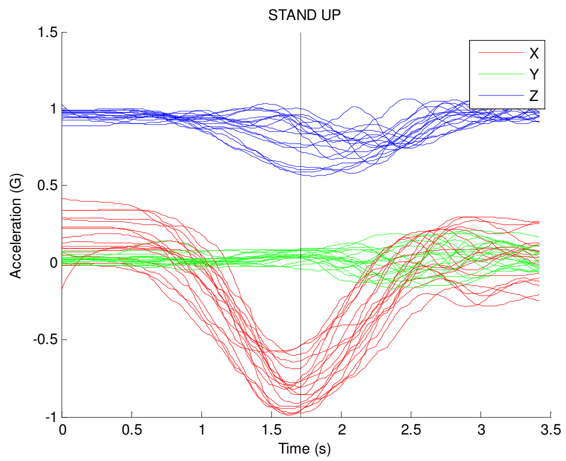

Fig.3 Stand up action

B. Sit Down action

The action of sitting down a steady stand state takes between 1-3.5 seconds (100-175 samples). of Fig. 3 show 18 actions of sitting down and its 3 acceleration signals. The action of sitting down could be seen as an inverse of standing up but the movement is not a negative of standing up, visually analyzing the Fig.3 and Fig.4 it shows this will be a challenge for the lightweight classifier to discern between the 2 actions, because the real data don't seems that different.

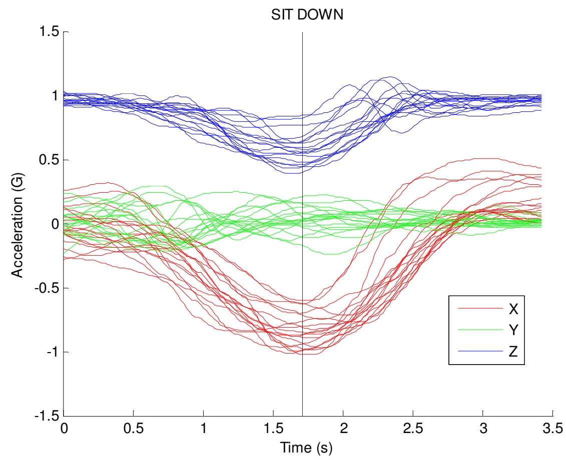

Fig. 4 Sit down action

C. Walk

The training data for the walk action Fig.5 starts in a local minimum of the Z acceleration axis, the duration of a step is variable between 0.5 seconds and 1.5 seconds, instead of searching for individual steeps the classifier is trained to search for walking action, later we can compute the number of steps dividing the time of walking action by the mean of a walk step duration.

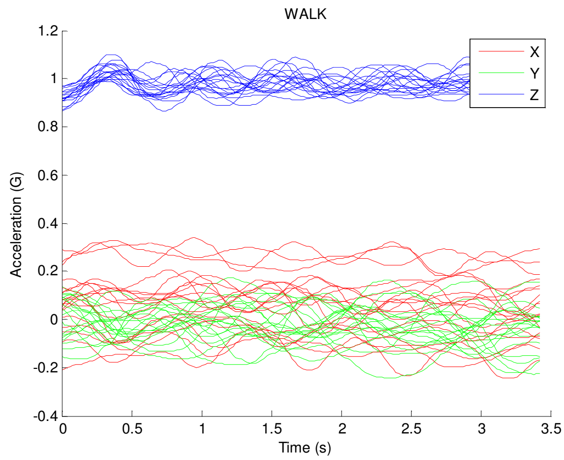

Fig. 5 Walk action

D. Steady stand

The steady stand signal Fig. 6 has no significant peaks or timing but is not constant either, it's a low frequency and amplitude oscillating signal, the center of the input window used to feed the classifier is arbitrary set to the center of the steady sample.

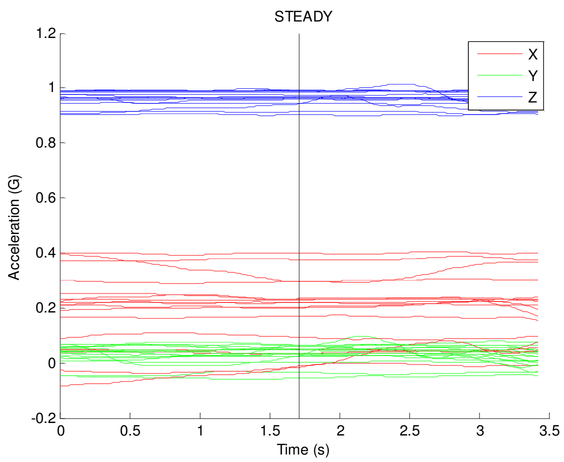

Fig. 6 Steady stand action

E. *Training Data*

From the whole data logs only a small portion of walk actions is used for training, the size is variable but in each of the 18 files is lower than half of the amount of experimental data labeled as walking available. In the sit down action half of the 32 actions are used for training. In the case of standing up all the 18 actions are used for training and later for validation because the accuracy is not good in this particular action and we tried to use all the available data to increase performance. This training data is used by the TREE and SVM classifiers.

IV. TREE CLASSIFIER

The tree classifier [3] is capable of identifying the different events from the training group; a single classifier gives the output from 1 to 4. The input of the classifier is a sequence of points from the accelerometer data. The basic signal is a sequence a sequence of X axis samples, next a sequence of Y axis samples and finally a sequence of Z axis sample. The best wide of this histogram is evaluated between ranges from 3 to 171 samples, this wide means the length of a single axis sequence so actually the input of the classifier is this wide value multiplied by 3.

A. *Preprocessing*

The preprocessing of the accelerometer data before entering the classifier can be statistical characteristics, angle calculations, the acceleration module, increments and so on. The only preprocessing used in the tree classifier is a FIR low pass filter implemented inside the DSPic before sending the data.

B. *Post Processing*

The tree classifier has problems to differentiate between stand up and sit down, giving false sit down positives while standing up event, even thought the number of false sit down positives are lower than the successful stand up classifications. A rule set used to solve this problem is that a positive sit or stand signal from the classifier triggers a counter (once triggered set to 0) that counts sit and stand events until a walk or steady event is detected, then the one with higher counter determines the action that starts at the first sit/stand action and ends when a walk/steady event is detected. This decision method introduces a small delay to the classifier output but improves the classification results.

C. *Results evaluation*

The tree classifier is applied on the whole 18 data logs, from the number of sample equals as half window wide to the length of data log minus half of window wide. The output of the classifier is compared to the labeled action and its correlation can be seen in Fig. 7.

Fig. 7 correlation between tree classifer otput versus label in function of wide of window size, solid lines are after post processing the classifier output and dashed lines arare raw classifier output

The post processing rule improves the correlation between the labeled action and the classifier, the best correlation 0.79 is achieved at 18 samples histogram window size.

Using accuracy as number of positive identification divided by labeled events, and false positives ratio as false positives divided by number of positive events, for each action. The means of accuracy on the 18 files while using a wide of 18 samples on the window size is shown in the Table 1.

Action	Accuracy (%)	False positive ratio (%)
Steady	79.22	22.01
Walk	89.91	21.34
Stand up	44.09	24.31
Sit down	61.1	20.24

Table 1 Tree Classifier accuracy

While looking at the accuracy is important to notice that the label is a good reference but not an absolute truth because, the training data is centered in the case of sit and stand on the middle off the signal, but on the label the action is labeled as sit down during all the action and not only in the middle of the action, the difference in width of these outputs is an explanation about the moderate accuracy.

The classification of a 26600ms sample using a trained tree classifier takes 628ms in a average PC, this code is not speed optimized but the duration gives a hint about the processing power required to implement it in real time.

V. SVM CLASSIFIER

The support vector machine SVM is a machine learning tool and has that is used for solving binary classification problems [5][6]. The kernel function of the SVM used in this problem is the Gaussian Radial Basis (RBF) Function kernel [7], other polynomial kernels from order 1 to 3 have been tested but they offered results worse than the RBF. The tuning of the SVM involves deciding the wide of the input window, the Sigma used, the box constraint, and also the preprocessing of the signal. We evaluated the wide of the input window versus the correlation with the labeled pattern (video based identification).

The SVM classifies input data into 2 groups by finding the an optimal separating hyperplane between the two data sets, but since our intention is to classify 4 actions, we need to run 4 classifiers in parallel and create a rule to decide a single output based on the 4 classifiers output.

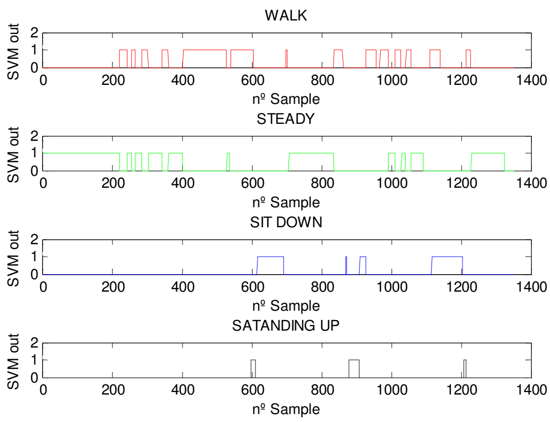

Fig. 8 Raw SVM output

The output of each classifier is or a positive action or no action, sometimes the four classifiers give no action, or sometimes more than one classifier gives a positive action, we can see more than one positive identification events in Fig. 8.

The rule is needed to obtain an output (second signal in Fig. 9) that has a good correlation with the training pattern (third signal Fig 9). Part of the rule consists of setting a value of dominance for each signal, standing up > sitting down > walking > steady. When all classifiers give negative output the output is keep from earlier output, and finally a walking event is maintained during 300 milliseconds if the following events are labeled as quiet, because the classifier gives to many steady states while walking.

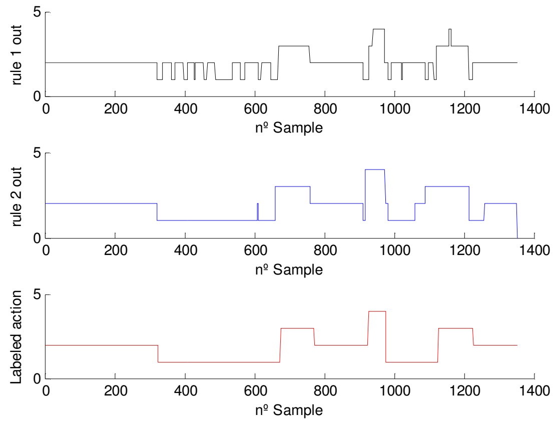

Fig. 9 SVM output after being processed

The performance of the SVM classifier using of the rule to combine the 4 classifier outputs is measured in all the 18 data logs, using different window sizes. The size of the window is from 3 to 167 consecutive acceleration samples in 2 sample increments. The figure 10 shows that the max correlation mean value 0.788 is at wide 28, and the max absolute correlation (1 single experiment) value is 0.9084 at wide 28, and finally the highest min correlation (in all 18 files) is 0.6878 at 28. The duration in time of the best average results window size (28 samples) is 0.560 seconds.

The classification of a 26600ms sample takes 7232ms in a average PC, this code is not speed optimized but the duration gives a hint about the processing power required to implement it in real time. The code scripts to train and evaluate the classifiers are written in Matlab m-type files and run on Matlab 2006b.

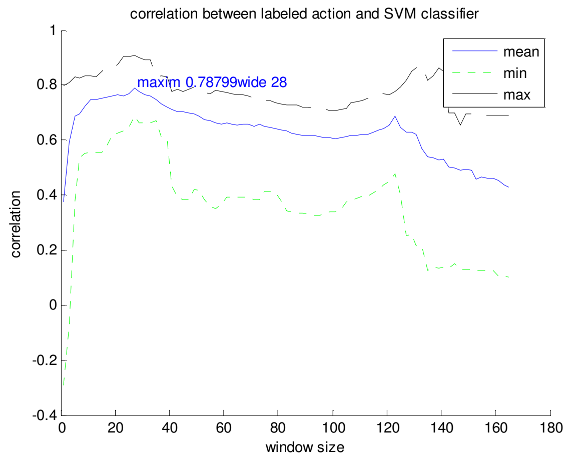

Fig. 10 SVM correlation of SVM output vs window size

VI. CONCLUSIONS

The processor load to implement a Tree classifier is much smaller than a SVM implementation, so it enables online signal processing by small microprocessors.

The next objective is to implement this classifier in a sensor node that measures and process online while it is being used. This interactive device can give some feedback to the user like giving advices or reporting a schedule to be complete in rehabilitation.

Using only one triaxial accelerometer to monitor human activity has advantages like small size, wearable device and low system complexity but lacks separability, instead having more accelerometers allows simple activity identification using the orientation of different body segments.

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