ACTIVITY RECOGNITION FROM ACCELERATION DATA COLLECTED WITH A TRI-AXIAL ACCELEROMETER

Ioana FARKAS , Elena DORAN
Faculty of Electronics, Telecommunications and Information Technology, Technical University of Cluj-Napoca
Str. G. Baritiu nr. 26-28, Cluj-Napoca, Romania, Tel:+40264202380, Ioana.FARKAS@bel.utcluj.ro

Abstract: This paper proposes a high accuracy classifier for human activity based on data collected with a single tri-axial accelerometer mounted on the right part of the hip. The accuracy of this classifier is very important for detecting the postures. Therefore we use methods like acceleration magnitude and neural network and compare them to find the best solution.

Keywords: *Tri-axial accelerometer, activity recognition, acceleration magnitude, neural networks.*

I. INTRODUCTION

Monitoring health status and quality of life is an important factor for assessment activity from subjects living in the community. Accelerometers allow the assessment of physical activity for long periods of time, long enough to be representative of normal daily life. The assessment of physical activity in free-living subjects is very important to a complete understanding of relationship between daily physical activity and health.

Carlijn V.Bouten [1] used a tri-axial accelerometer to evaluate a relationship between energy expenditure due to a physical activity and body accelerations during different activity. Mathie [2] distinguished between activity states and rest states from daily movements using data collected with a tri-axial accelerometer mounted on the waist. She applied to acceleration data a method using acceleration magnitude, investigating three parameters: length n of a smoothing median filter, the width w of the averaging window and threshold. She obtained a good accuracy around 98%.

Yuichi [3] made a study of accelerometer mounting locations on the body and demonstrated the high differences that accelerometer placements can have on the measurements used in ubiquitous entertainment and health applications. Ignoring this factor will result in faulty interfaces, responsible for unfair physical activity gaming or erroneous physical activity recording.

Zang [4] combined a tri-axial accelerometer with a cell phone to use it for fall detection with KFD Algorithm. Fall detection was made especially for the elderly people who were living alone

The objective of this paper is to recognize different types of activity from the data obtained with a tri-axial accelerometer mounted on the right part of the hip of subjects who were performing different movements. We developed two types of detection. First type of detection was made with the threshold method and at the second type of detection we used a multilayer neural network classifier.

II. METHODOLOGY

A. *Instrumentation*

A tri-axial accelerometer mounted on the right part of the hip was chosen to perform the measurements.

The system used to collect the data was developed at Cogent Computing Applied Research Centre, Coventry University, and is described by Brusey and Rednic et.al [6-9]. This system was composed of a Gumstix Verdex XM4-bt as a main processing platform, with a footprint of 80 x 20 x 6,3mm and weight of 8 g, containing a 400MHz Marvell PXA270 XScale CPU, 64MB of RAM, 16MB of flash memory, Bluetooth communications on-board and it also provide USB host, a 60-pin Hirose I/O connector, a 120-pin MOLEX connector and 24-pin flex ribbon connector. One acceleration sensor board was connected to the Gumstix device via an expansion board which provides I2C bus connection and connects to the Gumstix via Hirose connector. The microcontroller is a Microchip PIC24FJ64GA002 while the accelerometer used is a ST Microelectronics LIS3LV02DQ which is capable of measuring acceleration over a bandwidth of 640Hz for all axes. The peak current consumption is 0.65-0.8mA, supply voltage 2.16-3.6V and shut down mode consumption 1-10uA.

The data collected from the accelerometers were passed from Gumstix via Bluetooth to a computer. The power supply was from 4 batteries of 1.8V each. Using wireless method, we don't have restrictions on the mobility of the subject or location of the monitoring device. In Figure 1 a block diagram, the system and sensor body placement are shown.

B. *Algorithm development*

The first method for detecting periods of activity in the signal was made in Linux Ubuntu with Python software. Data collected with the tri-axial accelerometer mounted on the right part of the hip were passed through a high pass filter (HPF) with a cut off frequency Fc=0.25Hz (as low as possible) to remove gravitational acceleration component.

Manuscript received May 2, 2011; revised June 17, 2011

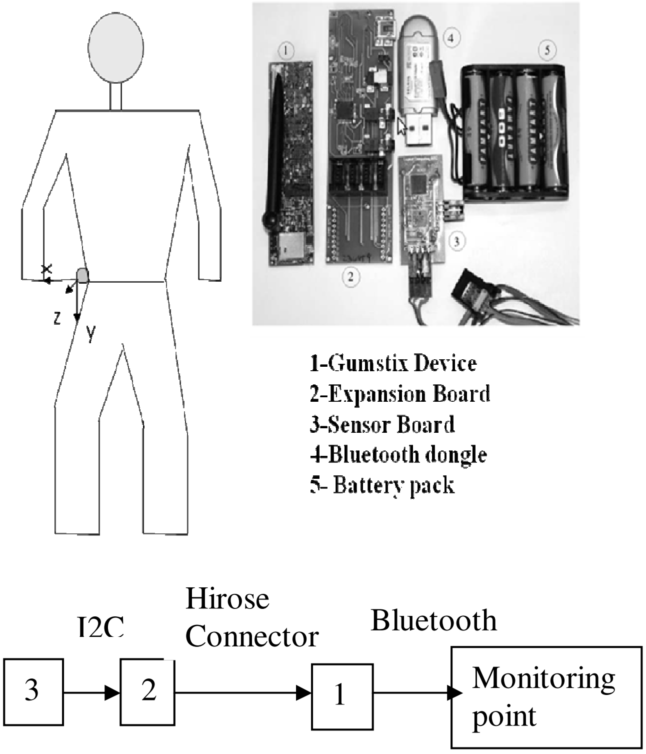

Figure 1. A block diagram, the system used to collect the data and the body sensor placement.

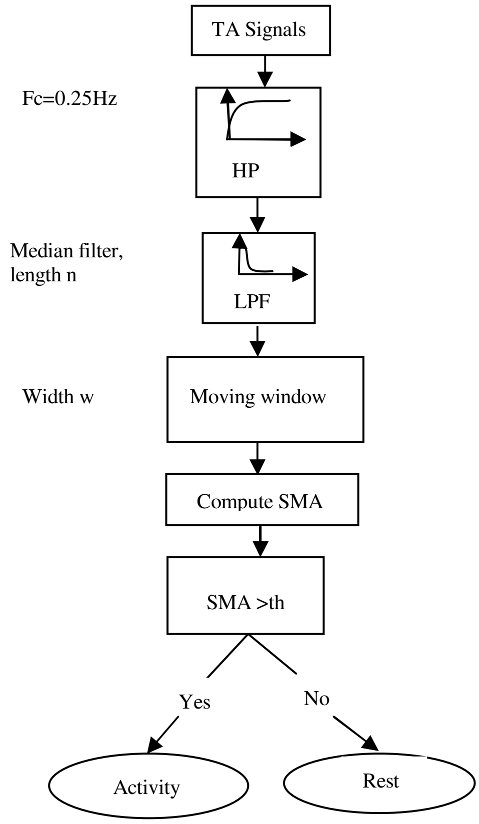

Figure 2. Activity and rest classification.

We applied a low pass filter (LPF) with the length n=19 samples and a non-overlapping moving window of width w=0.1 seconds to remove high frequency noise. In order to be able to make a difference between an activity and rest state we calculated the feature signal magnitude area (SMA). We applied a threshold method to the signal magnitude area for classifying data into dynamic and static postures. A diagram of using this procedure is shown in Figure2.

Second method of detecting periods of activity in the signal uses neural networks and was made in Windows using Matlab software. Following the method of Jhun-Ying [5] we eliminate gravitational component from the original signal by applying a high pass filter to obtain the body acceleration. Because of the long and continuous sequence of the acceleration data, it is difficult to analyze and recognize activity in the signal without any manipulation. In order to make easier the work with that amount of data we cut the acceleration data into many overlapping windows of the same length. From each window features were extracted from filtered acceleration data, with windows at the same size. For each window signal magnitude area and average energy (AE) are calculated. By applying a threshold to the signal magnitude area and average energy we were able to find the target vector which was $[1,0]^T$ for each window representing a static activity and $[0,1]^T$ for each window which belongs to a dynamic activity. In this way we were able to obtain the target vector in unsupervised mode. In the next step we windowed in the same way the original data without applying any filter and we calculated eight important features: mean, absolute deviation, root mean square, standard deviation, variance, correlation between axes, energy and interquartile range.As a result we have eight features for each axis and because tri-axial accelerometer collects data from three axes we have a total of 24 features for each window.

Because the number of features is too high we need to reduce this number. One of the well known methods for multivariate statistical analysis which can transform the original features into a lower dimensional space is the principal component analysis (PCA).

To find the number of feature that we need for classification of activity and rest state we follow 4 steps as [5], obtaining the loadings, calculating the cumulative contribution, applying common principal component (CPC) and support vector clustering (SVC) algorithms to indicate which features have similar contribution by selecting the corresponding points closest to the centroids of the K clusters and identifying their corresponding original features. In this way we obtain the number of feature that we need.

After we have set the features data together with the target vector we can classify rest and activity states by applying pattern recognition neural network.

C. Data Analysis

We have to take in consideration the position of the tri-axial accelerometer on the body and the postures of the subject because the output of the tri-axial accelerometer depends on it. The output of the tri-axial accelerometer is determined by its orientation to the gravitational vector if the subject is in a resting state. The movement component is composed from several different accelerations, generated by the translational and rotational body movements. A typical sample of data is shown in Figure 3. In order to classify data into activity and rest periods, first we apply the threshold method where signal magnitude area must be compared with the threshold. Before computing signal magnitude area we need to "clean" the data to obtain the best accuracy. Thus, we apply a high pass filter to remove the gravitational component. The cut-off frequency of the filter is Fc=0.25Hz. Figure 4 shows a sample of data after the high pass filter has been applied. Now we have to remove the high frequency noise from the signal by applying a low pass filter to the signals of a length of n=19 samples and a non-overlapping moving window with a width of w=0.1 seconds. Including both effects of magnitude and duration of the signal we were able to calculate SMA defined as the sum of the areas (magnitude x time) under module, of the corresponding signals in each plane, normalized to the length of the signal

$$SMA = \frac{1}{t}\times\left(\int_t |x(t)|dt + \int_t |y(t)|dt + \int_t |z(t)|dt\right),(1)$$

where x, y and z are the acceleration signals from the tri-axial accelerometer.

The threshold was set $th = 1.5ms^{-2}$ and if the measured value of the signal magnitude area exceeds the preset-threshold than the subject is engaged in an activity, otherwise the subject is engaged in a rest mode. A sample of data of SMA compared with the preset threshold is shown in Figure 5.

The second method for classifying the original data into periods of rest and periods of activity was done using pattern recognition neural network. For applying the network we need a set of data with a computed target vector. In order to do this, we applied a high pass filter to remove gravitational component from the data and in this way body accelerations from the signals were obtained. Because the set of data was a long and continuous sequence, this set was windowed in overlapping moving windows of 50%. Extracting features from window is an effective way for classifying the data. The features that we need to obtain the target vector were signal magnitude area and average energy.In this case signal magnitude area was calculated as [5]:

$$SMA = \frac{1}{w}\left(\sum_{i=1}^{w}|x_i| + \sum_{i=1}^{w}|y_i| + \sum_{i=1}^{w}|z_i|\right), \qquad (2)$$

where w is the window length, in our case w=10, x_i, y_i and z_i represent the *i*th body component of the x-, y- and z-axis samples in a window.

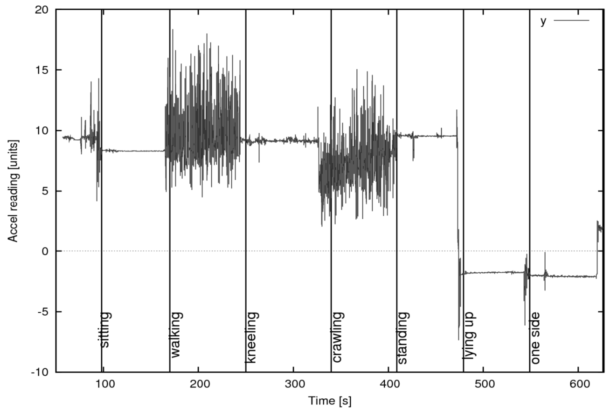

Figure 3. A typical sample of the data collected, showing vertical axis accelerations from a subject performing part of the test sequence. Activity segments were timed and correlated with time stamp of signal. Different activities are indicated.

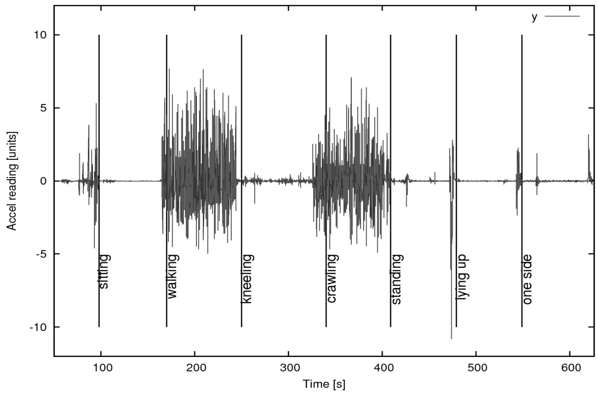

Figure 4. Sample of data after the vertical axis was passed through the high pass filter (HPF).

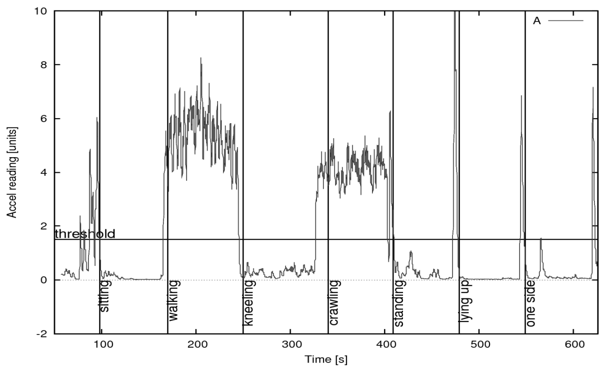

Figure 5. A sample of SMA data signal compared with the threshold

The second feature, average energy (AE), is calculated as average of the energy over the three axes: the sum of the squared discrete FFT component magnitudes of the signal in a window. A preset-threshold th = 2.5 was chosen for SMA and a threshold th1=0.02 was chosen for AE. If the SMA and AE are smaller than the thresholds, than we consider that the subject is in a rest state and the target vector $[1,0]^T$ will be assigned to the corresponding window. If the SMA and AE are bigger than the thresholds then we consider that the subject is engaged in an activity and the target vector $[0,1]^T$ will be assigned to the corresponding window. In this way we obtained a set of data coresponding to the target vector. Next step of this method is extracting features from the windows. The eight features are: mean, correlation between axes (3), energy (4), interquartile range (5), mean absolute deviation (6), root mean square (7),variance (8), standard deviation (9).These features were calculated by formulas:

$$correlation(X,Y) = \frac{\operatorname{cov}(X,Y)}{\tau_X \tau_Y}, \qquad (3)$$

where X,Y are the variables for x- and y-axes, τ-standard deviation and cov - covariance

$$energy = \frac{\sum_{i=1}^{w} |F_i|^2}{|w|}, \qquad (4)$$

where w is the length of the window, *i* is the *i*th FFT component.

$$INT = iqr(x). \qquad (5)$$

Interquartile range of the data for x-axes

$$MAD = \frac{1}{|w|}\sum_{i=1}^{|w|} |X_i - n|, \qquad (6)$$

where X_i is acceleration instance ,n is the mean value of X_i and w - the length of the window

$$RMS = \sqrt{\frac{1}{|w|}\sum_{i=1}^{|w|} x_i^2}, \qquad (7)$$

where x_i is acceleration instance, and w - the length of the window

$$Variance = \frac{1}{|w|-1}\sum_{i=1}^{|w|} (X_i - n)^2, \qquad (8)$$

where X_i denotes acceleration instance ,n - the mean value of X_i and w - the length of the window

$$St.Dev = \sqrt{\operatorname{var}}, \qquad (9)$$

where var is the variance.

Because the tri-axial accelerometer collects signals from all the three axes we calculated 24 features (3axes x 8 features) for each window of acceleration data. The dimension of the features data set (FDS) is too big to deal with it and because of this we take in consideration dimensionality reduction technique for feature extraction by applying principal component analysis method to reduce the original features into a lower dimensional space. First it was applied PCA to the features set to obtain the loading matrix. Because only the first principal components are sufficient to represent the features set we need to find out which are the most representative. In order to do this cumulative contribution relation (10) was calculated [5]:

$$cumContribution(k) = 100 \times \frac{\sum_{i=1}^{p} \lambda_i(k)}{\sum_{i=1}^{n} \lambda_i(k)}, \qquad (10)$$

where $\lambda_i(k)$ is the *i*th singular value of the covariance matrix of the *k*th FDS item.

Cumulative contribution is usually $\geq \varepsilon$ where ε is within 70-90%. Then we choose $p = \max(p_k)$, where p_k ,is the number of the first principal components. A new loading matrix U_k was obtained, $n \times p$ and the columns for this new loading matrix are the first p columns from the original loading matrix. Singular value decomposition (SVD) algorithm was applied to the matrix H represented by relation (11), which is the common principal components loadings represented by the eigenvectors:

$$H = \sum_{k=1}^{N} U_k U_k^T. \qquad (11)$$

It results in the decomposed matrix H:

$$H = VSV^T, \qquad (12)$$

where S is the diagonal matrix $n \times n$, whose diagonal elements are the singular values of H, and V is the corresponding eigenvectors (components) of H. CPC loadings are denoted with V_p representing the first p columns of V. Support vector clustering algorithm was performed on the row vectors V_p as data points to find the number of clusters K. The most representative features were obtained by selecting the most corresponding points closest to the centroids of the K clusters and their corresponding features were identified. In our case from 24 features we were able to identify the first 3 features corresponding to static activities and 4 features corresponding to dynamic activities. Periods of rest and activity were classified using pattern recognition neural networks with the toolbox from Matlab. As input vector we used the first four features extracted from each window and as target input we used the target vector obtained earlier. 30% of data were used by the network during training, and the network was adjusted to this error. 35% of data were used to measure network generalization, and to halt training when generalization stops improving. 35% of data has no effect on training, in this way providing an independent measure of network performance during and after training. In the hidden layer 5 neurons were selected.

D. Experimental procedure

Three different experiments were conducted in which four healthy subjects (males, age 23-27) performed a sequence of specific postures and movements while wearing the tri-axial accelerometer on the right part of the hip. The procedure was the same for all four subjects. Each subject carried out eight different activities. The sampling frequency was Fc=10Hz (10 samples per second).

The sequence for the first experiment was: standing (1 min), sitting (1 min), kneeling (1 min), crawling (1 min), walking (1 min), lying with the face down (1 min), lying with the face up (1 min), lying on one side (1 min). The protocol took around 9 minutes to complete. The sequence for the second experiment was: standing and moving the hands (3 min), sitting at the office and working at the computer, arranging things on the table (4 min), kneeling and arranging some boxes on the floor and taking things from the boxes and putting them back (2 min), crawling (2 min), walking and moving hands (3 min). The protocol took around 15 minutes to complete. The third experiment was composed of this sequence: sitting at the office and working at the computer, cleaning the desk, arranging things on the desk (1 min), kneeling and arranging boxes on the floor, taking some things from the backpack and putting them back (1 min), crawling (1 min), standing and moving the hands (1 min), lying with the face down (1 min), lying with the face up (1 min) and lying on one side (1 min). The protocol took around 9 minute to complete. Activity states were considered to be walking and crawling postures. Rest states were considered to be sitting, standing, kneeling, lying with the face down, lying with the face up and lying on one side.

As it can be seen from the second and third sets of experiments during the postures of rest states we introduced some additional movements (movements that can exist in real live in that kind of postures) that shouldn't have any influence on the classification of activity and rest states.

III. EXPERIMENTAL RESULTS

Four healthy subjects were wearing the system and each of them where following three different sequences. For the first method of classification, the first sequence has eight postures of 1 minute each, a total of 32 postures in 36 minutes. Data obtained from the tri-axial accelerometer were passed through high pass filter (HPF), low pass filter (LPF) and then signal magnitude area was calculated and compared with the preset threshold to classify periods of activity and periods of rest. An accuracy of 98.09% was obtained for periods of activity and 99.41% for periods of rest without any activity included.

The second sequence where movements were included in periods of rest was composed of five different postures, a total of 20 postures in 60 minutes. The data were processed as the first sequence and an accuracy of 99.82% for periods of activity and 99.62% for periods of rest were obtained. The time of each posture was longer than first sequence because we wanted to see if any difference appears between longer periods of time and shorter periods of time for this algorithm.

The third sequence has all the eight postures of 1 minute each, a total of 32 postures in 36 minutes. This sequence has also the daily movements included in periods of rest that shouldn't influence the accuracy of the rest states. For this sequence an accuracy of 99.08% for periods of activity and 98.75% for periods of rest were obtained. A total accuracy for all the three sequences was found 99.23% for all the periods of activity, 99.26% for all the periods of rest and the total average of 99.24% as is shown in Table 1.

The second algorithm was applied for all sets of data. First the target vector was computed by applying a high pass filter to original data and then windowing the resulting data. For each window the feature signal magnitude areas and average energy were calculated and compared with the preset thresholds.

All the eight features were calculated for all the three axes of the tri-axial accelerometer and principal component method was applied in order to reduce this number (24 features) to be able to classify data into periods of rest and periods of activity. In this case only the first four features have enough information to able to classify data. Pattern recognition neural network was applied to classify data and as an input vector the first four features were used and the target vector. 30% of the input vector, were used for training, 35%

	Activity	**Rest**
Regime 1 (4 subjects, 32 postures, 36 min)	98.09%	99.41%
Regime 2 (4 subjects, 20 postures, 60 min)	99.82%	99.62%
Regime 3 (4 subjects, 32 postures, 36 min)	99.08%	98.75%
Total Average (4 subjects, 84 postures, 132 min)	99.23%	99.26%

Table1. The accuracy obtained with the first algorithm

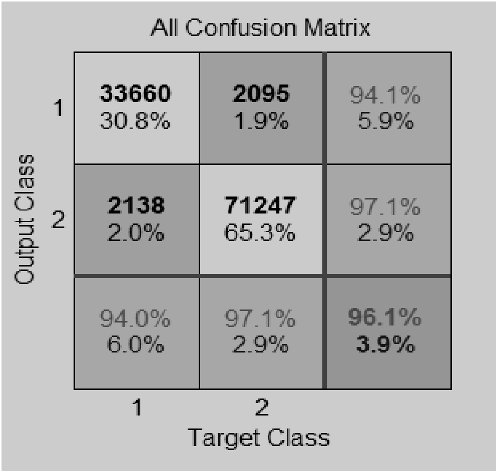

Figure 6. Confusion Matrix of classification for periods of rest and activity.

were used for validating and 35% were used for testing. The hidden layer was chosen with 5 neurons and the processing time was 2.35 minutes. Figure 6 shows that the accuracy for periods of activity (line 1) was found 94,1% and for periods of rest (line2) 97.1% with an average of 96.1% (line3). From a set of 109140 windows (35755 activity windows and 73385 windows representing rest state), 33660 were correctly classified as activity and 2095 windows were incorrect classified, as rest state. 71247 windows were correctly classified as periods of rest and only2138 windows incorrectly classified as activity.33660 windows correctly classified as activity represent 30.8% from the set of data and 94.1% from windows that are activity state. The data correctly classified have the performance of 96.1% and 3.9 % wrong classified.

IV. CONCLUSIONS

In this work, the problem of accurately classifying periods of activity and periods of rest based on measurements from a tri-axial accelerometer mounted on the right part of the hip was explored. The experimental system is easily to wear, low cost and good accuracy. This system can be applied on the clothes, the tri-axial accelerometer mounted on the right part of the hip and the rest of the system put in a pocket without disturbing the subject who wears it during the daily movements. We were able to classify data with two different methods into periods of activity and periods of rest. First method is the threshold method, where a high pass filter and low pass filter was applied, signal magnitude area was calculated and compared with a preset threshold obtaining a classification of activity and rest of 99.23% and respectively 99.26% with a total average of 99.24%. Second method used a pattern recognition neural network classifier. First the target vector was calculated by applying a high pass filter. Splitting the data into overlapping windows of 50%, for each window signal magnitude area and average energy were calculated and compared with a preset threshold. After target vector has been calculated the input vector was necessary to apply the pattern recognition neural network. The original data collected with the tri-axial accelerometer were split into overlapping windows. Eight features were calculated for each signal from each window. Because the amount of data was too big we reduce this amount by applying a principal component analysis and the input vector was obtained with only four features from the initial 24 ones. Pattern recognition neural network algorithm was applied and the accuracy of activity and rest periods was found 94.1% and 97.1% respectively. We have considered the feature selection for reducing the number of significant features in order to increase the processing speed and the computing capacity. Even in these conditions, the classification accuracy has been improved in comparison with other methods used in literature [5]. From these two classifications methods it can be seen that the best result was obtained with the threshold method that is also simpler than the second one and faster to be applied

The results obtained by applying the proposed methods in this paper have better accuracy than the others presented in literature, where the best results belong to [2] with 99% for detection of rest and activity.

V. ACKNOWLEDGEMENT

Paper published in the Project development studies Ph.D. in advanced technologies “PRODOC” POSDRU/6/1.5/S/5 ID767.

REFERENCES

[1] C.V.C.Bouten, K.R.Westerterp, M.Verduin, J.D.Janssen "A triaxial accelerometer for the assessment of daily physical activity in relation to energy expenditure", *Engineering in Medicine and Biology Society, 1993. Proceedings of the 15th Annual International Conference of the IEEE*, pp.985-986, 2002.

[2] M.J.Mathie, J.Basilakis, B.G.Celler “A system for monitoring posture and physical activity using accelerometers”, *Proceedings of the 23rd Annual EMBS International Conference,* Instambul, Turkey, 2001

[3] Y.Fujiki, I.Pavlidis, P Tsiamyrtzis “Making Sense of Accelerometer Measurements in Pervasive Physical Activity Appliccations”,CHI2009~Student Research Competition, Boston, MA, USA, 2009.

[4] T. Zang, J Wang, P. Liu and J. Hou, “Fall Detection by Embedding an Accelerometer in Cellphone and Using KFD Algorithm”, *IJCSNS International Journal Computer Science and Network Securty,* Vol. 6, No. 10, Octomber 2006.

[5] J.Y.Yang, J.S. Wang, Y.P.Chen “Using acceleration measaurements for activity recognition: An effective learning algorithm for constructing neural classifiers”, Science Direct: Pattern Recognition Letters, Vol. 29, Issue 16, pp.2213-2220, 2008.

[6] J. Brusey, R. Rednic, E.I. Gaura, J. Kemp, and N. Poole, Postural activity monitoring for increasing safety in bomb disposal missions. *Measurement Science and Technology*, 20(7):075204 11pp, 2009.

[7] J. Brusey, R. Rednic, and E. Gaura, Classifying transition behaviour in postural activity monitoring. *Sensor & Transducers Special Issue*, 17:213_223, 2009.

[8] R.Rednic, E.I.Gaura,J.Brusey “Wireless sensor networks for activity monitoring in safety critical applications”. *Technical Proceedings of the 2009,* pp.521-525, Huston, S.U.A, 2009.

[9] R. Rednic, E. Gaura, and J. Brusey, ClassAct: Accelerometer-based Real-Time Activity Classi_er. *Sensors & Instrumentation KTN: Wireless Sensing Demonstrator Showcase (WiSIG)*, 2009.