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Human activity recognition using neural networks

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Abstract
This paper presents research made for independent daily life assistance of elderly or persons with disabilities using IoT technologies. The scope is to develop a system that allows living for as long as possible in familiar environment. This will be possible by wider spread of assistive technologies and the internet of things (IoT). With aim to bring together latest achievements in domain of Internet of things and assistive technologies in order to develop a complex assistive system with adaptive capability and learning behavior. We can use IoT technologies to monitor in real time the state of a patient or to get sensitive data in order to be subsequently analyzed for a medical diagnosis. I present the state of my work related to the development of an assistive assembly consisting of a smart and assistive environment, a human activity and health monitoring system, an assistive and telepresence robot, together with the related components and cloud services.

Keywords: Assistive technologies, e-Health, activity recognition, artificial neural networks, assistive and tele presence robots

1. Introduction

In the present world, millions of people die every year due to lack of information about their health. Increased costs in the healthcare system could be reduced, if it would give more attention to disease prevention through regular assessment of health status and their treatment in the early stages. As a result of this situation, many researchers are trying to develop technologies to improve the quality of human life using IoT technologies [1-8]. Our research reflected this trend, to help gather information to assess health and provide information to properly trained personnel in diagnosing patients. We can use IoT technologies to monitor in real time the state of a patient or to get sensitive data in order to be subsequently analyzed for medical diagnosis.

Human activity and health monitoring system

I have developed a data acquisition module prototype, presented in Fig. 1, for activity and health status parameters acquisition [9]. It is composed of a ChipKit Max32 microcontroller development board, a 3 axes accelerometer sensor, a heart rate belt sensor and communication modules. This module is part of assistive assembly consisting of a smart and assistive environment, an assistive and telepresence robot, together with the related components and cloud services [10-15].

The acquired data could be stored on the on-board SD card module and/or can be transmitted via wireless communication to a remote server for storage and processing. The 3 axes accelerometer, incorporated into a Texas Instruments Chronos smart watch, is used for identifying the acceleration of the body in reference with x, y and z axes. The heart rate belt senses the heart beats and converts the data into a heart rate and transmits the values via the communication units to the gateway unit. The communication modules implement three different the wireless protocols: Simplicity for communication between Chronos watch and its access point, Blue Robin for communication with the heart rate belt and WIFI for communication with the gateway unit.

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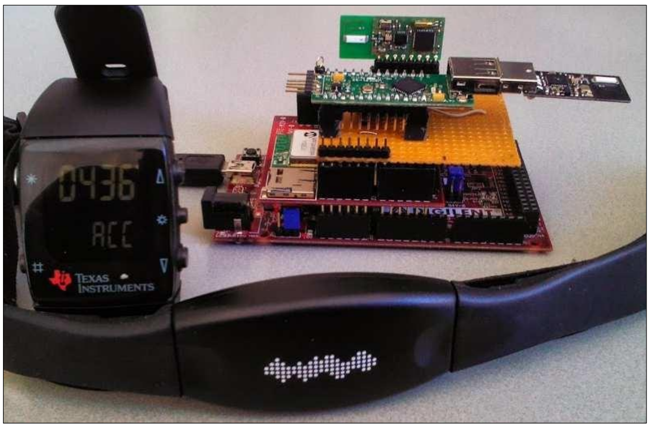

Fig 1: Human activity and health monitoring system prototype.

Patient's vital signs can be monitored continuously and remotely, thus allowing early recognition of exceptional situations and thereby avoiding worsening of health.

The acquired data can be used for artificial neural networks training, and conclusions can be drawn about the patient's current health status. The recognition system is implemented on a PC, on which the Matlab software is running. The Matlab implementation is considered the first step before migrating towards the more dedicated hardware-software environment implemented in the FPGA circuits. The recognition system is tailored for meeting the expected recognition rate accuracy of 90%. It basically consists of an artificial neural network modelled in Matlab and a series of pre-processing modules (filtering, normalization, feature extraction).

Activity recognition based on neural networks

Considering the nature of the data provided by the sensors used in the body posture recognition system a recognition system should use an algorithm that is capable to deal with nonlinear data, is able to reconfigure, learn and generalize and also to tolerate the inherent errors (noise). The most important recognition algorithms developed so far have a biological influence and can be grouped in the following categories: artificial neural networks, fuzzy systems, genetic algorithms, neuro-fuzzy systems. All the enumerated systems share these main characteristics: parallel computation, learning, generalization and flexibility. In the following, the artificial neural networks are analyzed.

Finding the right topology of the Artificial neural Network (ANN) for a specific application is a challenging task and only through several simulations of different ANN topologies, in terms of numbers of neurons per layers and numbers of hidden layers, can be found the optimum one. In our case after several tries we obtained good result using a two-layer feed-forward network, with sigmoid activation function on both the hidden and output layers. The training function adopted was *trainlm* that updates the weights and biases values of the neural network according to Levenberg-Marquardt optimization. The training method is the fastest backpropagation algorithm offered by the Matlab. The performance function is set to the MSE function. It measures the networks performance according to the mean of squared errors.

A. Arm posture recognition

The first step, towards the body posture recognition, was the arm postures recognition system modelled in Matlab. We have defined 6 arm postures as are presented in Table 1. As input device we used the accelerometer embedded in a smart watch (Chronos system developed by the Texas Instruments) wore on the wrist (Fig.2).

Table I: Posture definition

1. Arm downwards	4. Arm horizontal backward
2. Arm upwards	5. Arm horizontal forward rotated upwards
3. Arm horizontal forward	6. Arm horizontal forward rotated downwards

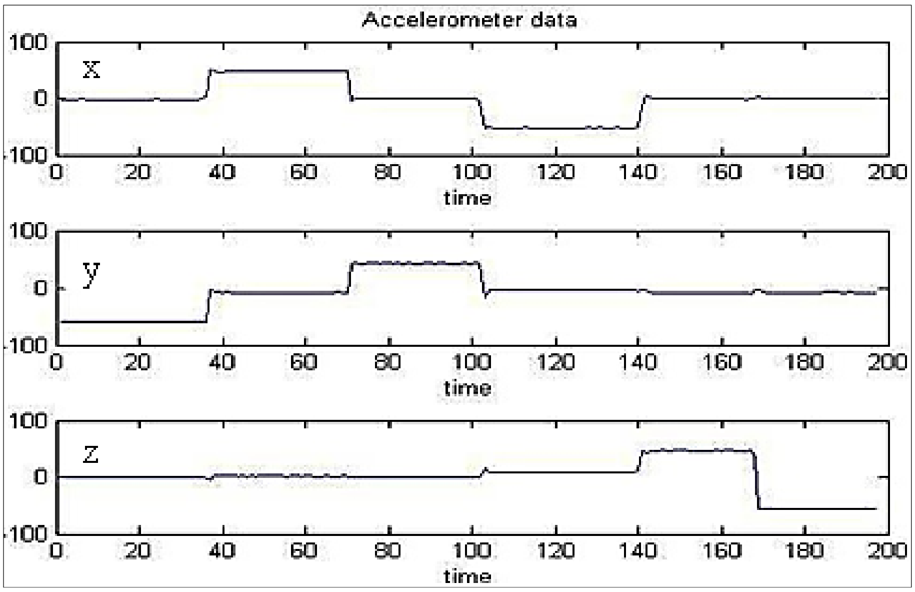

Fig 2: Data acquired from acceleration sensor for the 6 arm postures.

As the input data vector was formed from 3 sets of data, one for each axes of the accelerometer, the neuron numbers in the input layer was set to 3. Considering that there are 6 postures to be recognized, six neurons have been placed on the output layer. For the neuron from the hidden layer have been tried different numbers. We finally chose a two layer architectures with:

- 2 layers FF-BP
- 10 neurons on the hidden layer
- 6 neurons on the output layer
- Levenberg-Marquardt as training algorithm
- MSE for performance function evaluation

For testing purpose we have chosen data from training set, the obtained recognition rate was 100%.

B. Body posture recognition

The body posture recognition system is responsible for recognizing within a predefined list of postures. We defined 5 body postures presented in Fig. 3. Fig 4. presents the acceleration data on the 3-axis recorded for the five defined postures. Acceleration data are supplied by the Chronos watch, fixed on chest.

We designed and tested a Feed-forward Back propagation network with two layers having 10 neurons on hidden layer and 5 neuron on output layer. The recognition rate was 99.96%. Simulation result is presented on Fig. 5.

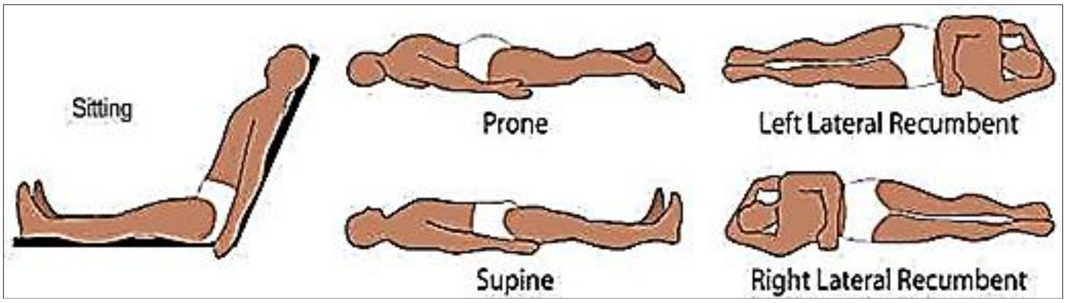

Fig 3: Body postures definition.

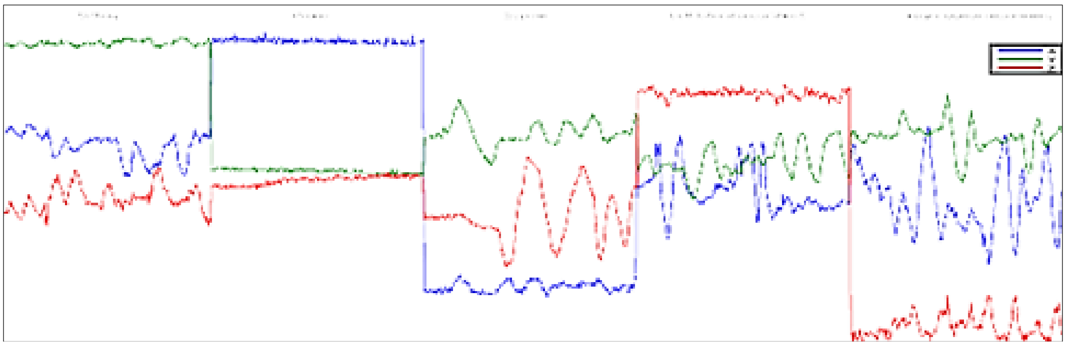

Fig 4: Data aquired from acceleration sensor for the 5 body postures.

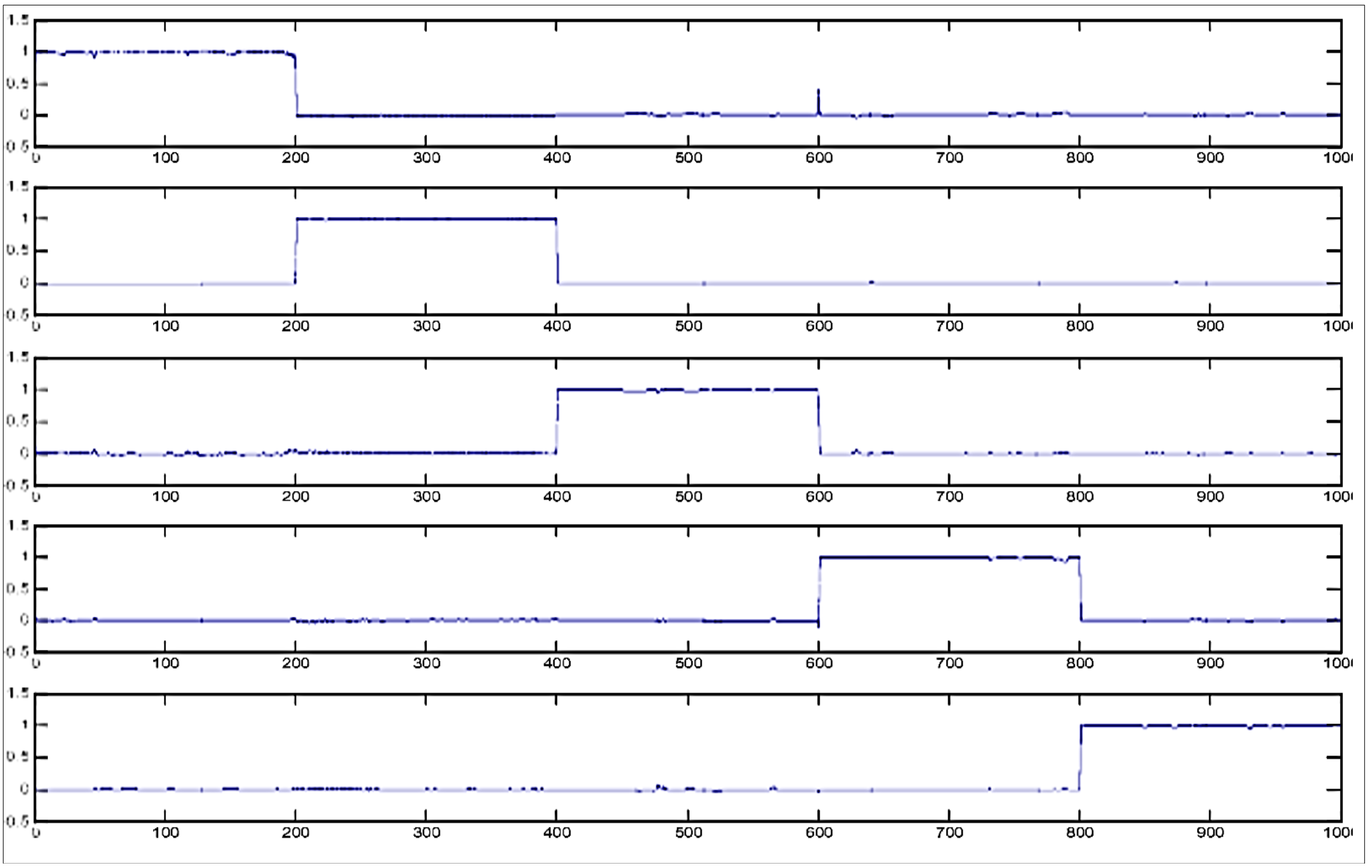

Fig 5: Neuron ouputs for the 5 body postures.

C. Activity recognition

A new data set was acquired and includes ten postures presented in Fig. 6. The data set was split up in 3 subsets for training, validation and testing. The dimensionality of the input vector dictates numbers of neuron on the input layer vector (which is four: 3 sets of data from the 3 axes of the accelerometer and one set from the heart rate sensor). The output layer has 10 neurons because we adopted for the output neurons the “one to n” coding for showing the recognized posture and there are 10 posture to be recognised as follows:

1. Standing
2. Supine
3. Left lateral recumbent
4. Right lateral recumbent
5. Prone
6. Walking (forward)
7. Walking (backward)
8. Running (forward)
9. Running(backward)
10. Seating

After several tests we found that for the hidden layer 10 neurons seems to be enough for a good recognition rate. The resulting neural network architecture for the activity recognition is shown in Fig.7. The testing sets were chosen from the training set and was setup from 10 times 500 consecutive vectors representing each activity to be recognized. So the first neuron will recognize first 500 sample and so on. The recognition / errors are displayed in Fig. 8. Total number of errors was only 456, meaning a 99,088% recognition rate.

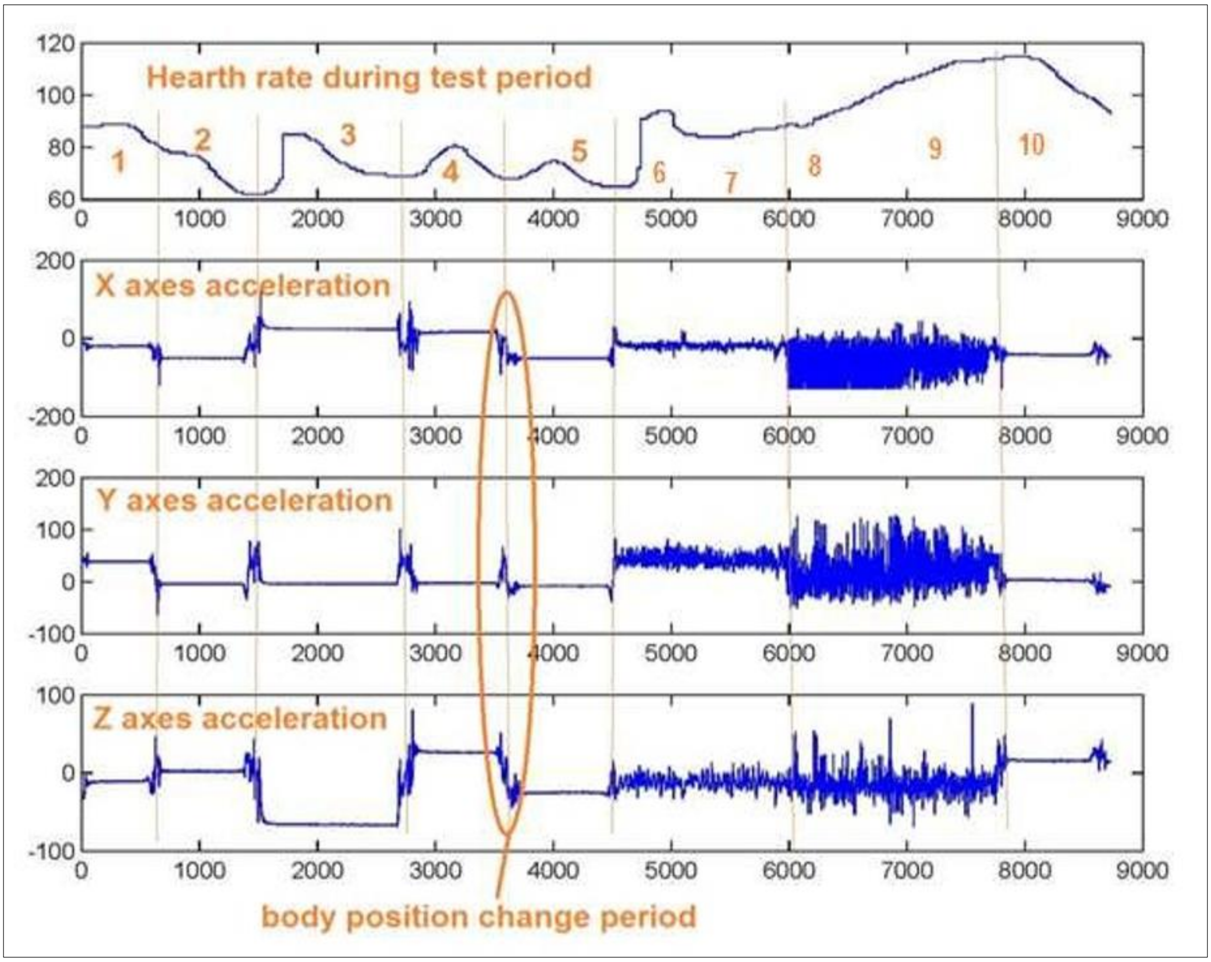

Fig 6: Data aquired for the 10 activities.

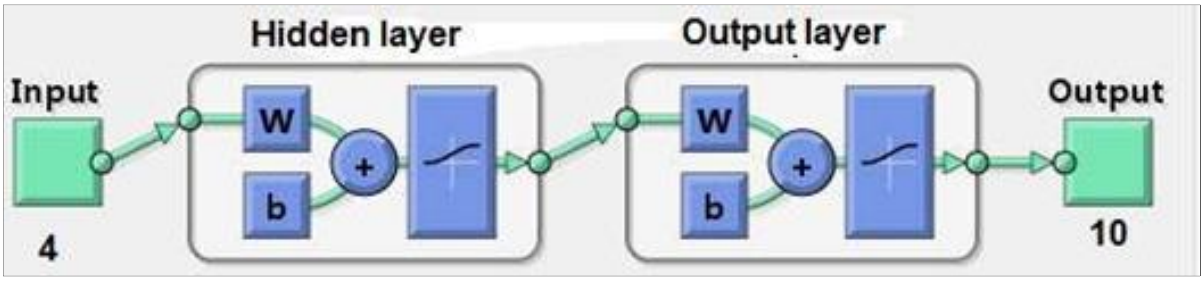

Fig 7: ANN architecture for the activity recognition.

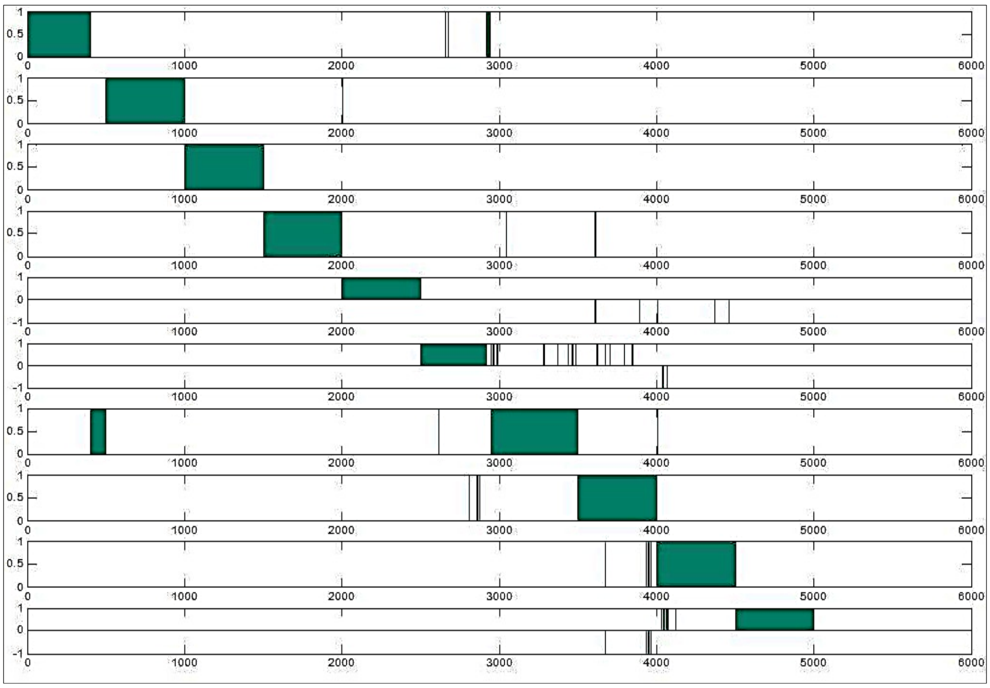

Fig 8: Output layer neurons response to the testing set.

D. Differentiating dynamic activity from static

For differentiating the dynamic activity from static, requires some processing on the raw data set. The literature reports the using of features that include Mean value, Variance, Correlation coefficients, Energy, Frequency-Domain Entropy, Cepstral Coefficients, Log FFT Frequency Bands, etc. [16-22]. Other authors report the use of the autoregressive (AR) modelling coefficients, the Signal Magnitude Area (SMA) and Tilt Angle (TA) as key features to distinguish dynamic activity from static [23-24, 25-26].

We have chosen to use standard deviation values for differentiating the dynamic activity from static. The results are shown in Fig.9 for each of the accelerometer's axes and for the pulse rate. The standard deviation was calculated over a window of 50 samples (it is considered that the data acquisition was made at 20 Hz and within 1 sec there is at least 1 step made). Analyzing the figure can be seen that by setting the right threshold (red line) for the standard deviation, the static – dynamic postures discrimination can be easily differentiated.

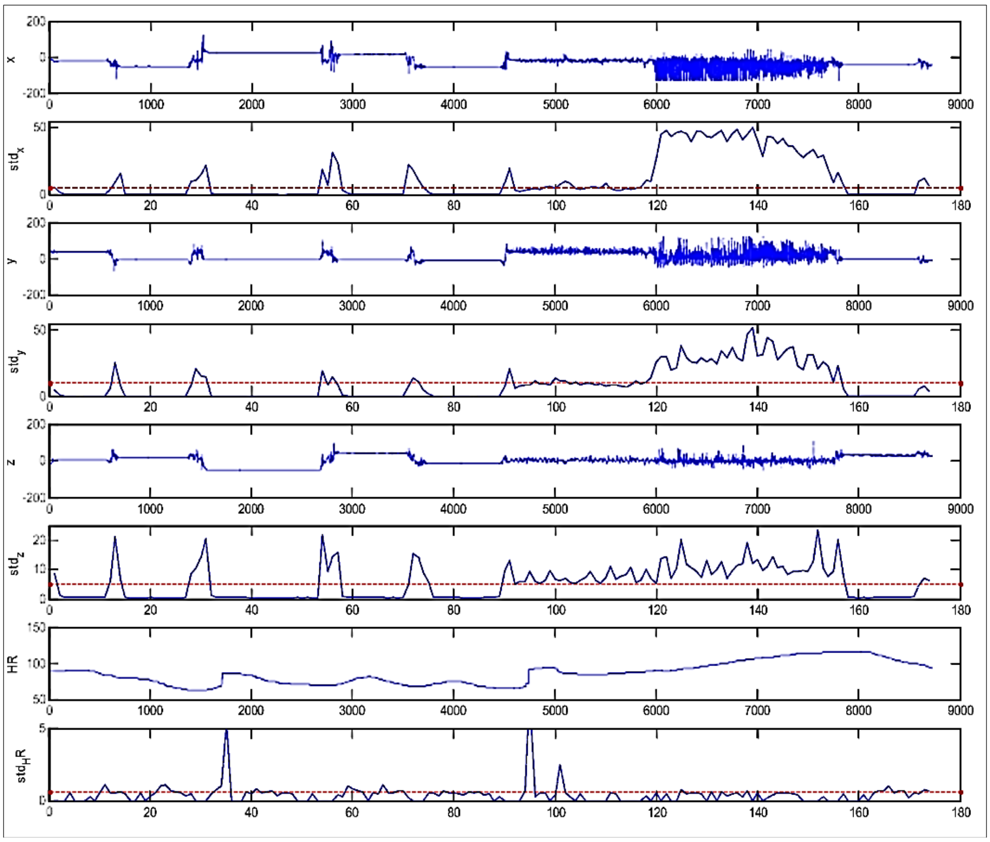

Fig 9: Differentiating dynamic activity from static using standard deviation.

E. Recognizing the walking and running activities

For recognizing the walking and running activities, further relevant features have to be extracted from raw data set. Also using some processing algorithms on can determine further properties related to the activities, as for example using FFT transform we can determine the stepping rate. Fig. 10 shows the initial acceleration signal (a) FFT transform of the signal for walking period (b) and the FFT transform of the signal for running. The FFT transform was used to determine the stepping Rate of a person as the most dominating frequency in the acceleration signal's spectrum and was approximately 1.4 respectively 2.2 steps/second.

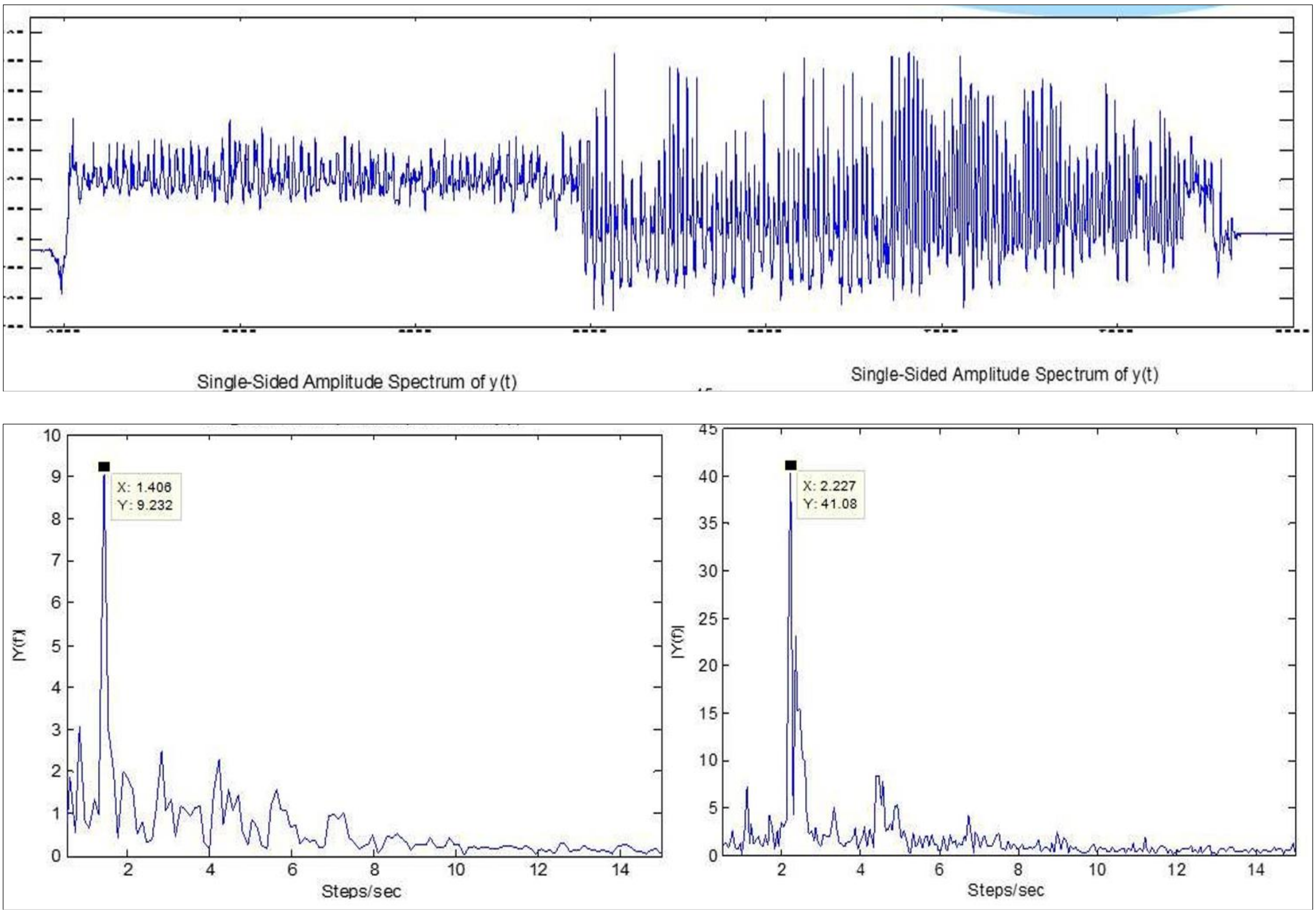

Fig 10: Using FFT for steping rate evaluation.

Conclusions

The presented work shows my work related with human activity monitoring and recognition. I Tried to implement and test recognition system for arm posture, body postures and simple activities like standing, sitting, walking, running, etc. We obtained very good recognition rates on data sets from used for training. Further test must be made on new test date collected in different circumstances and from different persons.

In future development we will add new sensors (ECG, EMG, breath, etc.) to our monitoring module and will use sensor data fusion and fuzzy logic rules for activity recognition. Further research is needed for simulation of more types ANN for activity/health status recognition. The best performing ANN will be used for hardware implementation using FPGAs.

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