Neural network design for Ambulatory monitoring of elderly

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ABSTRACT

Home health care with compact wearable units sounds to be a convenient solution for the elderly people living independently. This paper presents a method to detect fall from the other activities of daily living and also to classify those activities. This kind of ambulatory monitoring enables them to get an emergency help in the case of the fatal fall event and can provide their general health status by observing the activities being performed in daily life. A tri-axial accelerometer sensor is used to get the acceleration anomalies associated with the user's movements. The three axis acceleration data are transferred to the base station sensor node via an IEEE 802.15.4 compliant zigbee module. The base station sensor node sends the data to base station PC for an offline processing. This work shows the feature set preparation using the principal component analysis (PCA) for the designing of neural network. The work includes the most common activities of daily living (ADL) like Rest, Walk and Run along with the detection of fall events from ADL. The angle from the vertical is found to be the most significant feature parameter for classification of fall while mean, standard deviation and FFT coefficients were used as the feature parameter for classifying the other activities under consideration. The accuracy for detection of fall events is 86%. The overall accuracy for ADL and fall is 94%.

Keyword

Accelerometer, Activity classification, Principal component analysis, Neural network

Ⅰ. Introduction

A recent study has shown that the number and share of the population aged 65 and over will continue to grow steadily over the next decades [1]. With less number of care givers, the healthcare of elderly population living independently, is a challenging task for the modern healthcare system. Also an indication of the activity level performed by the people not only makes them aware of their general health status but also imparts a more active life style. In the series of studies for ubiquitous healthcare, the use of compact, low-cost sensors can help in long term care with less expenditure without disturbing the daily routine activities. The major risk factor associated with elderly is fall which can be fatal when no immediate care is available.

D.M. Karantonis et al. [2] presented an algorithm to classify the rest, movement, fall and posture of the person (Standing, Lying sub postures, sitting) using accelerometer sensor in single hop communication environment. The system proposed majority of signal processing on the wearable unit. The algorithm was performed after the separation of bodily and gravity acceleration components.

Ning Wang et al. [3]used Wavelet transform for simultaneously analyzing the time and frequency domain features for walk patterns and neural network for classification. The use of neural network classifier implied the generalization to the new user's data and hence making the system more flexible.

The most recent work is presented by Jafari et al. [4][5] which uses the structural pattern recognition with angle from the vertical axes. The work shows the performance of K-nearest neighbor method and neural network to match the received pattern with the fall pattern[5]. In an another work,[4] they used the linear feature set minimization for activity classification. They used a number of sensor at different body positions for this.

This work shows the classification of daily activities like rest, walk and run along with the detection of simple forward fall events. Both the time and frequency domain features were analysed to form a single feature set. A feature reduction method is also shown using the principal component analysis (PCA). A neural network was designed, trained and tested to show the final classification accuracies.

II. System Hardware and Software

The system architecture is based on the use of two sensor nodes[6]. One is the accelerometer sensor node at the user's end. This is used to capture the acceleration data associated with the activity being performed by the user. The other is the base station node to capture the data sent by the accelerometer sensor node. The base station sends the data, so received, to the base station PC via an RS-232 interface. In this work, Telos type sensor node, TIP710(Maxfor ,Korea) has been used as a resource for computation and communication while the Capacitive type Microelectromechanical Sensors (MEMS) tri-axial accelerometer MMA 7260 (Freescale Inc., USA) has been used for capturing the acceleration signal of the movement. The accelerometer sensor has a range of -6g to +6g and sensitivity of 200mV/g, g is here the acceleration due to gravity in m/s2. The sampling frequency was chosen as 50Hz[6]. Both the nodes have CC2420 2.4GHz ISM band radio which is capable to transfer the data at a rate of 250Kbps.

III. Methods

The data were collected by wearing the prototype sensor unit on chest. The acceleration data was sampled, quantized and packetized at the sensor unit and transferred to the base station node. The base station node transfers the data packets to the base station PC. The data, so received, at the base station PC consists of the three axis acceleration data in equivalent electrical terms. This data was analysed at the base station PC for the ambulatory monitoring of the person under observation. The MATLAB 7.4.0 has been used as a software platform at the base station PC. A neural network classifier design consideration are being shown in this research, These are as follows:

a. Data calibration and preprocessing: The de-packetized three axis acceleration data, at the base station PC is the equivalent acceleration values in terms of voltage levels. This needed to be converted back to the equivalent acceleration values in terms of gravity acceleration 'g'. This process is called as calibration. A linear calibration was performed on data[6].

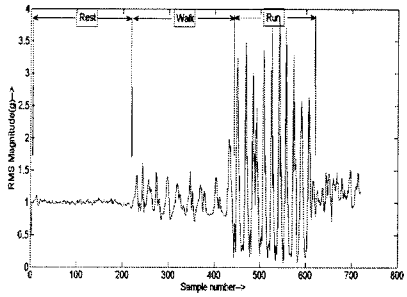

Fig 1. RMS of the three axis acceleration data for Rest, Walk and Run

The data so obtained consists of three axis bodily movement acceleration data, the gravity acceleration data and the spurious noise due to environment or circuitry involved. So a next step is to remove the unwanted noise signals from the data using filtering. We have used a moving average filter of order 3 to smoothen the data [7]. The filtered three axis accelerometer data was then combined to get a root mean square(RMS) value of the three acceleration levels[7]. The RMS acceleration data for a sequence of rest, walk and run is shown in fig.1.

b. Data classification: After the calibration and basic preprocessing the data was needed to be classified on the basis of the acceleration anomalies present. A neural network approach was used as a machine learning technique so that the classification results can be generalized for any unforeseen data as well.

For an efficient design of a neural network, data features should be selected so as the accuracy and feasibility is higher as well as the network is less complex(and hence faster). The next section discusses the feature set preparation and feature set reduction before classification using the neural network.

IV. Feature set preparation

For the classification, the preprocessed data was divided into a sequence of 256 samples to form one data block. The 256 data samples create a block of 5.1 seconds(for the sampling frequency=50Hz) and hence a single activity can be considered to appear in this small duration. Also the choice of size of 256 samples(a power of two) is also suitable for calculation of frequency domain features[9]. The selection of features from each data block is shown below:

a. Time domain features from data: As shown in fig.1, the three activities differ in their magnitude of accelerations and their ranges. This is also shown in fig.2 for mean, standard deviation, minimum and maximum value of the acceleration for the three activities involved. It is clear from the figure that these values can be used for classification of Rest, Walk and Run.

Also for detecting the fall event the angle from vertical axis has been found to be a more accurate observation as sometimes the magnitude of the same has been found to be overlapped with that of a run activity[7]. So the angle from the vertical at each sample point is included as the feature parameter in the feature set.

So, Time domain feature set(of size 260)={ Mean, standard deviation, minimum value, maximum value, 256 points of angle from the vertical } was created.

b. Frequency domain features: The frequency has been found to be a more accurate parameter for classification of ADL [8]. So a 256 point FFT has been calculated and the half part i.e. 128 points have been included as a frequency domain feature set.

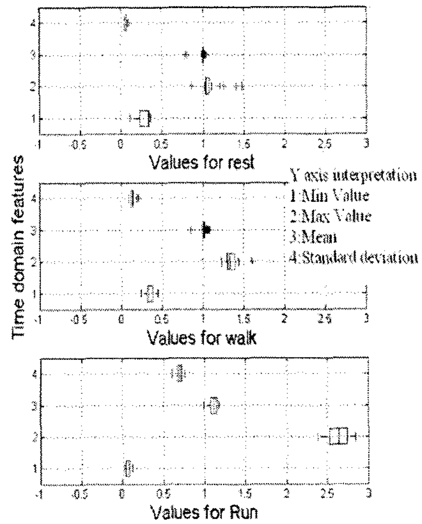

Fig 2. The time domain feature values for Rest, Walk and Run

c. Total feature set: The total feature set was created by combining the two sets i.e. time and frequency domain feature sets. So the total feature set size was of 388 points for each data block.

d. Feature reduction: If the classification were performed using a data set of size 388 points(for each of the observed data block), It would have taken a long time to train a neural network as well as a large number of neurons in each of the hidden layers. So a feature reduction was implemented. The motive of feature reduction was to reduce the size of the feature set and simultaneously retain the motion anomalies present in the feature set.

Feature reduction can be performed either by using a feature subset from the original feature set or by a feature transformation. The former method is simple but requires a lot of data statics to be analysed to count the importance of each feature for the classification while the latter one involves transformation of the feature set to new plane such that the transformed feature have a more descriptive power to order than the original feature set.

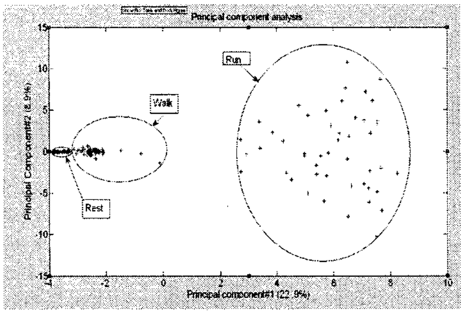

Fig 3. Principal component#1 versus Principal Component#2.

A feature transformation using principal component analysis(PCA) has been analysed for the reduction purpose[10]. A new set of variables, called the principal components, were calculated which were the linear combination of the original features. All the principal components were so calculated that they were orthogonal to each other, So there was no redundant information. The calculated number of principal components were the same as the original number of features in the feature set. But for the reduced feature set only those principal components were included which were found to have a variance of more than 0.2% of the total variance of the original data set. An analysis for principal component#1 and principal component#2 is shown in fig.3 for data of only rest, walk and run activity. The figure also shows the grouping of similar activities on the plane.

During the observation it was found that only 65 components were giving a variance of more than 0.1% of the original data and only 51 of them were giving a variance of more than 0.2%. Also from the manual retrogression it was possible to classify the data using a composite plot of different combinations of the principal components on plane.

Ⅴ. Neural network training and results

A neural network(NN) has been designed for the classification of the accelerometer data to one of the four categories i.e. rest, walk, run and fall. The network was designed with different number of layers and neurons in each of the layers. The classification accuracy for the various training and testing data sets with five fold cross validation have been observed to find the best design of the network iteratively. The Table 1 records the implementation results for each of the activity using Principal components, contributing more than 0.2% of the variance. The classification results using various approaches have been recorded in Table 2.

Table 1. The classification results obtained using the PCA resuction

Activity Performed ↓	Total number of data blocks considered	Number of data blocks classified correctly
Rest	49	49
Walk	49	45
Run	49	49
Fall	29	24
Rest, Walk, Run and Fall	176	167

Table 2. A comparison of the classification results obtained from various approaches

Method used	Activities considered	Classification Accuracy
Tilt Angle	Fall	66.6%
PSD and Median Frequency	Walk and Run	81.25%
FFT Coefficients upto 8Hz	Rest, Walk and Run	93.1%
NN Classifier(Using FFT coefficients only)	Rest, Walk and Run	83.96%
NN Classifier with Tilt angle	Rest, Walk, Run and Fall	83.2%
PCA of feature set including the time and frequency domain features	Rest, Walk, Run and Fall	**94.88%**

Ⅵ. Conclusion

The activity monitoring and fall detection system has been implemented using an accelerometer sensor node in a wireless sensor network environment. Both the time and frequency domain features were analysed for achieving the best classification. A feature reduction technique, for an efficient neural network designing, has also been shown. The overall classification accuracy of implementation was recorded as 94.88%.

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