Human activity classification using Neural Network

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ABSTRACT

A Neural network classification of human activity data is presented. The data acquisition system involves a tri-axial accelerometer in wireless sensor network environment. The wireless ad-hoc system has the advantage of small size, convenience for wearability and cost effectiveness. The system can further improve the range of user mobility with the inclusion of ad-hoc environment. The classification is based on the frequencies of the involved activities. The most significant Fast Fourier coefficients, of the acceleration of the body movement, are used for classification of the daily activities like, Rest walk and Run. A supervised learning approach is used. The work presents classification accuracy with the available fast batch training algorithms i.e. Levenberg-Marquardt and Resilient back propagation scheme is used for training and calculation of accuracy.

Keyword

Activity monitoring, accelerometer, neural network classification, FFT

Ⅰ. Introduction

The future vision of healthcare implies the monitoring of subjects over longer periods of time using wearable units. The advent of wireless sensor nodes resulted in interest in wireless health monitoring. One of the important part of wireless health monitoring is Physical activity recognition of the subject from a remote location.

A lot work has been done in this area, with the use of a combination of wireless sensor node and accelerometer as the wearable unit[1][2][3][6].

For the classification of the accelerometer data, a number of different approaches have been used since long. Mathie et al [1], used a single, waist mounted triaxial accelerometer and presented a hierarchical binary decision tree framework for movement classification. General distinction was made at top levels of the tree and more detailed classification at the bottom levels. The structure was modular and flexible, so the part of the tree can be pruned, reordered or extended.

Nishkam Ravi et al [2], showed the performance of base level and meta level classifiers using a single tri-axial accelerometer. The work also discussed plurality voting for accelerometer data classification for human activity detection.

Jonghun et al.[3], used several statistics like mean, standard deviation , skewness, kurtosis, eccentricity of accelerometer data as the features for classification.

Jonathan Lester et al [4], [5] presented a more detailed work using a shoulder mounted multi-sensor board. For the classification purpose, a total of 651 features were used which included linear and mel-scale FFT frequency coefficients, cepstral coefficients, spectral entropy, band pass filter coefficients, integrals, mean and variances. A hybrid approach was used for recognizing activities, which combined boosting and learning an ensemble of static classifiers with Hidden Markov models (HMMs) to capture the temporal regularities and smoothness of activities. The work was shown to be able to identify ten different human activities with an accuracy of 95%.

This paper presents the selection of a suitable algorithm, for human activity data received from a tri-axial accelerometer, among the existing neural network training algorithms. The work uses frequency as the only parameter for distinguishing the basic human motions like Rest, walk and Run. A comparison of the algorithms with number of neurons in hidden layer is also shown using a three fold cross validation approach.

II. Hardware

Telos type sensor node, TIP710 (MAX4, Korea) was used as computation and communication resource, Along with the Texas Instruments micro controller MSP430. TIP 710 has CC2420 2.4 GHz ISM band radio capable of data transfer at 250 kb/s. Capacitive type Micro-electromechanical Sensors (MEMS) triaxial accelerometer MMA 7260 (Freescale Inc., USA) was used with the above mentioned. 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 whole sensor unit was powered by two AA batteries. The whole unit is chest worn. The sampling frequency is chosen as 50 Hz [6].

The software for sensor unit was developed using nes-C as a programming language with Tiny-OS [8] as the real time operating system to make it compatible with sensor network.

III. Data Collection

A similar sensor node was on the base station PC to collect the activity data from the chest worn Sensor unit, described in section(II). Further data processing is done on base station PC using MATLAB. The data, so obtained, consists of both the body and gravity acceleration components. Therefore a preprocessing was needed before deriving classification features from it. The preprocessing involves-1) Calibration of the received samples in terms of 'g'-the acceleration due to gravity [7]. 2) Smoothening of the samples using Moving Average filter of size three. 3) A high pass filtering to filter out the gravity acceleration components from the smoothed data. An elliptical IIR high pass filter with cutoff frequency= 1 Hz, order=7, Passband ripple=0.01dB and stop band ripple=100dB, was used for the purpose.

3.1 Feature Selection and reduction

This paper presents the comparison of training performance and accuracy of the available neural network training algorithms for classification of the human motion data (including rest, walk and run) only on the basis of the frequency content. The Frequency present in the walking data has been found to lie within the range of 1.5-2.5 Hz and that in the running data within a range of 2.5-4Hz[6]. The only feature selected for the classification is FFT frequency coefficients.

The data for the neural network were gathered by taking the 128 point FFT (Fast fourier transform) of the 128 samples of preprocessed data. The choice of 128- points is taken so as to perform a fast computation of fourier transform [9] and include a data of sufficient duration (approx. 2.5 seconds) for classifying the activities. The FFT coefficients were then normalized so as to have mean=0 and standard deviation=1. A recent work [6] showed the difference in frequency content for the activities, under consideration, lie within a range of 5 Hz. Figure1 shows the frequency content present in the data of running activity and that most of the statistics in activity data lie upto a frequency of 5 Hz. So, only the initial FFT coefficients were used for classification. The sampling frequency was 50 Hz [7], therefore Initial 22 FFT coefficients (representing frequency upto 8.6Hz) were used as the reduced feature data for the neural network.

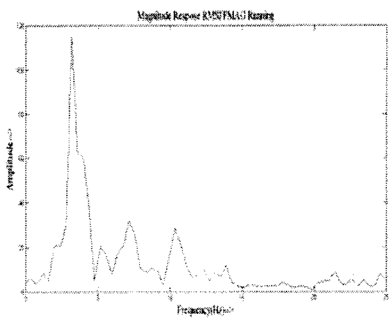

Fig. 1. Frequency Response of data during Running (shows peak within the range of 2.5-4Hz).

IV. Neural Network design Considerations

The neural network was initially designed with one hidden layer and one output layer. The training function for hidden layer is chosen as 'tansig' and that for output layer as 'purelin'. MATLAB neural network toolbox was used for implementing the same.

The data set consists of three activities , so three classes were defined- each representing a different activity. With the choice of 'purelin' function, for the output layer, The encoding used was as follows: the level 0 at output layer being classified as rest, 1 being classified as walk and 2 being classified as Run. This encoding required only one neuron in the output layer.

Several tests were conducted to make a comparison of training algorithms with varying the number of neurons in hidden layer. Out of the available neural network training algorithms, resilient back propagation (trainrp) and Levenberg-Marquardt (trainlm) were used because of their faster convergence property for moderate sized networks[9] as compared to gradient descent and quasi-newton algorithms.

Figure 2 and 3 show the training performance with every epoch for both the algorithms .

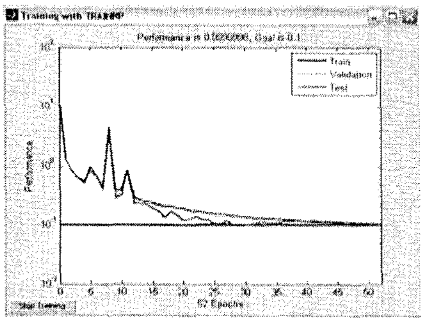

Fig. 2. Training performance of Resilient back propagation algorithm for user activity data.

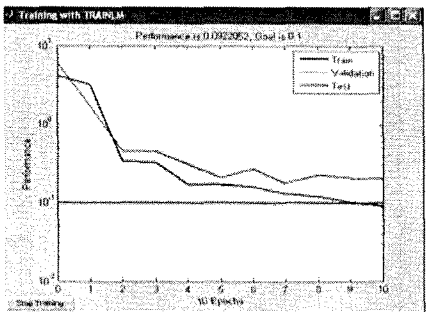

Fig. 3. Training performance of Levenberg- Marquardt algorithm for user activity data.

V. Neural network training and Results

The neural network was trained using three fold cross validation: In which three folds of data were created using a total of 150 data sets. Each fold consists of 50 sets having an equal number of rest, walk and run activity instances. Two of the data sets were taken at a time for training and the third one was used for testing.

Table 1 and 2 show the mean and standard deviation of the testing and training data classification rate with changing the number of neurons in Input layer. The tables show accumulated results for 9 runs of the training and testing data. Using more runs for comparison is used because sometimes the training got stuck at exactly 33%. This resulted in classifying all the data in just one activity. Using more training samples causes this situation to happen less frequently.

Table 1. Choice of Number of Hidden layer neurons for resilient back propagation algorithm

	Number of Hidden layer neurons(N)			
	3	5	7	9
Mean Training Classification Rate %	80.81	89.56	87.88	89.9
Training Standard Deviation	28.26	4.04	4.01	4.28
Mean Testing Classification Rate %	73.61	85.42	87.85	75.11
Testing Standard Deviation	30.42	11.27	9.37	30.47

Table 2. Choice of Number of Hidden layer neurons for Levenberg marquardt algorithm

	Number of Hidden layer neurons(N)			
	3	5	7	9
Mean Training Classification Rate %	55.44	74.52	78.56	73.51
Training Standard Deviation	39.85	28.63	29.57	29.53
Mean Testing Classification Rate %	52.89	68.86	77.08	77.08
Testing Standard Deviation	30.89	27.11	7.65	12.88

Table 1 showing for resilient back propagation algorithm(trainrp) and Table 2 for Levenberg-Marquardt (trainlm). A comparison of the results shown in table 1 and 2 imply that the resilient back propagation algorithm is giving more accuracy in classification rate (approx 87.88) than that for Levenberg-Marquardt algorithm(approx. 77.08). Also the standard deviation for classification rate are also less for resilient back propagation.

More classification rate is signifying that the activity has been classified correctly.

From the results, shown in tables 1 and 2, the best number of hidden neurons, for both the algorithms, are about 7 because it is giving more classification rate for testing data set. Also the standard deviation is about 4.01 for resilient back propagation, signifying the betterness of the resolution of classification for the testing data.

VI. Conclusion

The results show that among the available neural network training algorithms, the Resilient back propagation and Levenberg marquardt are giving faster convergence. Also the classification rate for human activity data using resilient back propagation algorithm is about 8 among 10 for optimum value of 7 neurons in Hidden layer. The classification is done using reduced number of FFT coefficients as features. The accuracy of classification along with the mobile, small sized and cheaper sensor node, making the system more susceptible to use for activity monitoring in ubiquitous healthcare environment.

REFERENCES

[1] M. J. Mathie, B.G. Celler, N.H. Lovell, A.C.F. Coster,"Classification of basic daily movements using a triaxial accelerometer", IFMBE: 2004, Medical & Biological Engineering & Computing 2004, Vol. 42

[2] Nishkam Ravi, Nikhil Dandekar, Preetham Mysore, Michael L. Littman, "Activity Recognition from accelerometer data", American Association for Artificial Intelligence 2005

[3] Jonghun Baek, Geehyuk Lee, Wonbae Park and Byoung-Ju Yun, "Accelerometer Signal Processing for User Activity Detection", KES 2004, LNAI 3215, pp.610-617.

[4] Jonathan Lester,Tanzeem Choudhury, Gaetano Borriello. "A Practical Approach to Recognizing Physical Activities", PERVASIVE 2006, LNCS 3968, pp. 1 - 16, 2006.

[5] Jonathan Lester, Tanzeem Choudhury, Nicky Kern3, Gaetano Borriello, Blake Hannaford, "A Hybrid Discriminative/ Generative Approach for Modeling Human Activities".

[6] Amit Purwar, "Activity monitoring of Elderly Person by Tri-axial Accelerometer in wireless sensor network" February 2008.

[7] Amit Purwar, Do Un Jeong, Wan Young Chung, "Activity Monitoring from Real-Time Triaxial Accelerometer data using Sensor Network", International Conference on Control, Automation and Systems 2007

[8] http://www.tinyos.net

[9] MATLAB, The language of Scientific Computing by Mathworks, Inc., www.mathworks.com