A Hybrid Method for Activity Monitoring Using Principal Component Analysis and Back-Propagation Neural Network

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***Abstract*— Human activity recognition is a useful topic of research as it recognizes various human activity ultimately helps in monitoring of patients in hospitals, elderly people at home etc. In this work a hybrid method using PCA and ANN is proposed for activity classification. Principal component analysis is used to find the important features from a number of features. In this work 381 features are selected from 561 features. Selected features are used as input to the ANN based classifier to recognize different human activity. The accuracy of the proposed activity classification method is 96.8%. Hence the proposed PCA and ANN based hybrid method can be used effectively for human activity recognition.**

Keywords—Artificial Neural Network, Human activity recognition, Principal component analysis, Smart Sensors.

I. Introduction

In real life there are many scenarios in which human activity recognition is helpful. Activity recognition can be defined as recognizing a person's actions such as standing, sitting, walking, laying down, walk upstairs, walk down stairs etc. Activities can be recognized using the data obtained from the body worn sensors. Now a day's smart phones have been a good tool for sensing purpose. Various researchers have been suggested various techniques for human activity recognition some of which are discussed below.

Wearable devices allow to capture diverse range of physiological and functional data for applications in sports, wellbeing and health care. Deep learning is a technique belongs to machine learning which involves working with algorithms based on the structure and functions of the brain which is used to infer and extract information from large data sets. In [1] combination of two types of features, shallow and learnt, is done to show that the modern day devices are capable of human activity recognition. This can be done by getting the computation time from various low-power devices such as wearable devices and IoT. Transferring the already learned knowledge from an already existing to new environment has proven to be a more practical, efficient and cost-effective approach while building contextual models for new smart environments. This approach reduces the data collection effort. Models trained via feature based knowledge transfer framework can even outperform non-transfer learning models is suggested in [2]. Recent advances in wireless sensor networks have created a possibility of tending to human needs by recognizing and analyzing their current activities. In [3] a framework that efficiently recognizes human activities in smart homes based in spatio-temporal mining technique is proposed. An approach is proposed by combining human activity into a multilevel framework for human activity and social role identification in [4].

Participants are grouped in pairs and each person gives feedback and modifies his/her behavior according to the feedback received from the other participant. This exchange of feedback between the pair of participants takes place simultaneously until the interaction goals are met. In [5] a method is proposed to show how a participant in a dyadic interaction adapts his/her body language to the behavior of the other participant, given the target for the interaction and context. Recently, attributes have been analyzed and treated as high-level semantic information which will help us is achieving efficient and accurate classification. Multitask learning is one of the methodologies used to achieve this goal, as suggested in [6]. Acceleration based human activity recognition has generated a lot of interested and has been a key area of focus. In [7], an approach which uses a spectral-geometry based algorithm is implemented for acceleration-based human activity recognition. This study introduces a new approach to implementing assistive smart homes. An intelligent agent architecture and intention recognition (IR) mechanism that may be used to form an ambient assisted living (AAL) system to assist with ADLs within smart homes (SH) is proposed in [8].

In this work a hybrid method for activity recognition is proposed using PCA and ANN. Performance of the activity recognition method is enhanced to some extent using proposed method.

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II. TECHNIQUES USED

A. Principal Component Analysis (PCA)

PCA identify smaller number of uncorrelated variables from a large set of data. Hence the size of the data is reduced without any significant loss of information. There are certain factors required to obtain PCA such as mean, variance, co-variance, Eigen vectors etc. Let Xi be each term and n be the total number of terms, then the mean M and the variance V is calculated from the equation (1) and (2) respectively.

$$M = (X1+X2+X3+...+Xn)/n \quad - (1)$$

$$V=((X1-M)^2+(X2-M)^2+...+(Xn-M)^2)/(n-1) \quad -(2)$$

The co-variance Vc between two terms Xi and Yi can be calculated using equation (3).

$$Vc=[((X1-Mx)(Y1-My)+(X2-Mx)(Y2-My)+(X3-Mx)(Y3-My)+...(Xn-Mx)(Yn-My))/(n-1)] \quad -(3)$$

where Mx is the mean of the X data set

My is the mean of the Y data set.

PCA method generally involves the following steps:

1)Fetching the data.

2)Subtracting the mean.

3)Calculating the covariance matrix.

4)Calculating the eigenvectors and eigenvalues of the covariance matrix.

5)Choosing components and forming a feature vector.

6)The new data set is derived using the following formula:

FinalData = RowFeatureVector * RowDataAdjust

where RowFeatureVector=transposed matrix.
RowDataAdjust =mean adjusted data transposed.

B. Artificial Neural Network (ANN)

Artificial neural network (ANN) is a pattern recognition and classification tool used in various fields of engineering. The architecture of the ANN contains unit like input, weight, bias, transfer function, layers etc. A simple neural network is shown in Fig.1. In Fig.1 x1, x2, …, xn are the inputs, w1, w2, …, wn are the weights, b is the bias, f is transfer function and y is the output. In this work feed forward back-propagation neural network is used as human activity classifier based on work done in [a-c]. Back-propagation network is a multi-layer neural network which propagates the error backward to obtain the desired output. The detail design of proposed methods is given in the section below.

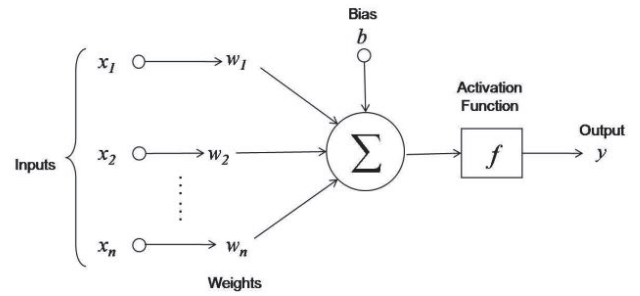

Fig.1. Simple Neural Network.

III. PROPOSED METHOD

Proposed PCA and ANN based human activity recognition method is described in the flowchart shown in Fig.2. Detail description of the proposed method is shown in subsection below.

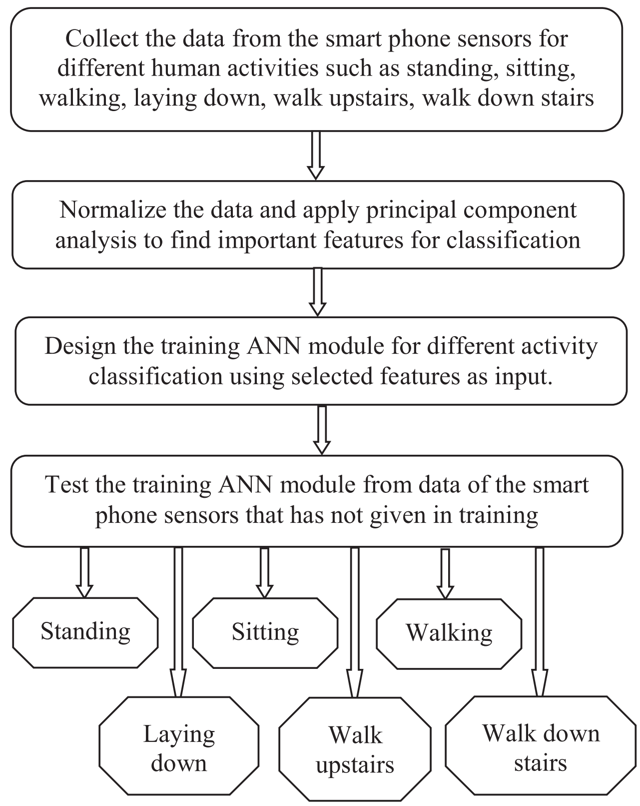

Fig.2. Flowchart of the proposed method.

A. Data Description

The data set used for validation of the proposed method has been obtained from UCI machine learning repository [11]. The data has been collected from volunteers between age group of 19-48 years wearing Samsung Galaxy S II smart phone. Acceleration and angular velocity of the signals at a sampling rate of 50Hz using the phone accelerometer and gyroscope has been collected [12]. Signals were then processed with a median filter and a 3rd order low-pass Butter-worth filter with a 20 Hz cutoff frequency. The features are calculated from input samples. A total of 561 features are obtained after feature extraction. The data set has been divided to 2 groups, 70% of the data are used in training and remaining 30% are used for testing.

B. Proposed Method using PCA and ANN

The input features obtained consist of 561 attributes which is too large. Hence principal component analysis is applied to obtain the appropriate features. The attributes which has contribution in classification less than 0.0003% has been removed from input features based on the highest accuracy obtained. From 561 attributes 180 attributes has been found to contribute less than 0.0003% in classification. Hence 381 attributes are selected as input features for the human activity classification. The input features are then given as input to the feed forward back-propagation neural network. From all the data collected 70% are used for training. There are 6 target classes each correspond to one activity such as [1 0 0 0 0 0 0] for walking, [0 1 0 0 0 0] for walking upstairs, [0 0 1 0 0 0] for walking downstairs, [0 0 0 1 0 0] for sitting, [0 0 0 0 1 0] for standing and [0 0 0 0 0 1] for laying down. In this work feed forward back-propagation neural network with Lavenberg Marquardt training algorithm has been chosen as basic neural network architecture based on the work done in [13-15]. After many hit and trial optimal network is chosen best on the highest accuracy in recognizing the activity. The optimal training neural network is shown in Fig.3. From Fig.3 it can be observed that final neural network architecture is a 3 layered structure which has 20 neurons with tan-sig transfer function in hidden layers and purelin transfer function in output layer. Fig.4 shows the confusion matrix obtained for training. The diagonal matrix shows the correctly classified data and others shows incorrect classification. From Fig.4 it can be observed the training accuracy is 100%. After training the network it is tested with remaining 30% of the data. Test results are shown in the section below.

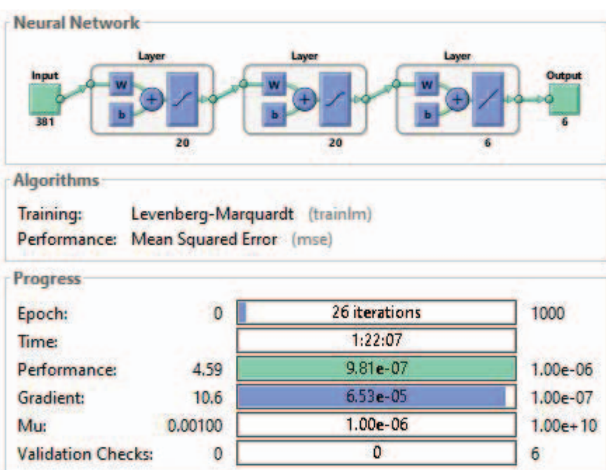

Fig.3. Training Neural Network.

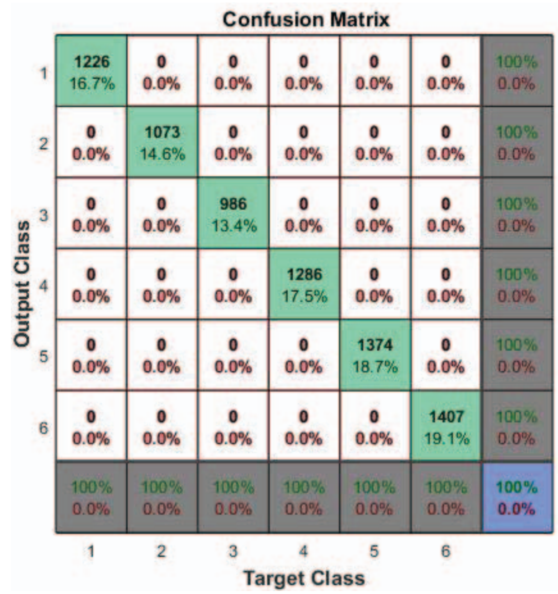

Fig.4. Confusion Matrix obtained during Training

IV. RESULT AND DISCUSSION

Proposed PCA and ANN based method has been tested with various test samples. Performance of the proposed method has been evaluated in terms of percentage accuracy, correctly classified data, mis-classified data etc. The performance of the proposed method is described in the section below.

A. Selection of Optimal Number of Input Feature

The proposed method originally have 561 input features from which 381 input features are selected using PCA. The optimal number of input features are decided based on the testing accuracy. Table I shows the performance of the method varying input features. It seems that the network with 381 input feature has highest testing accuracy of 98.6% among all the features considered. The number of correctly classified data is 10205 and misclassified data is 94. Fig.5 shows the testing confusion matrix which has 98.6% accuracy. Hence 381 input features are taken as optimal input features.

TABLE I SELECTION OF INPUT FEATURE

Contribution of attributes > x %	**Number of Input Features Selected**	**Training Accuracy (%)**	**Testing Accuracy(%)**	**Correctly Classified Samples**	**Misclassified Samples**
10	1	95	85.0	9534	765
1	8	100	91.0	10034	265
0.1	97	100	93.3	10102	197
0.01	207	100	95.4	10163	136
0.001	339	100	96.2	10187	112
0.0003	381	100	96.8	10205	94
0.0001	406	100	96.5	10196	103

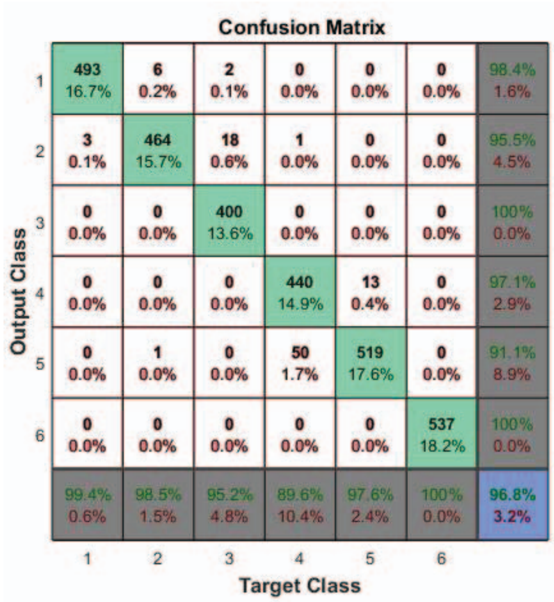

Fig.5. Confusion matrix of the test samples.

B. Selection of Mean Square Error Goal

The proposed activity recognition method has mean square error (mse) as the performance measure. The optimal mse is decided after training the network with various mse. The network with highest training and testing accuracy is chosen as optimal mean square value. Table II shows the performance with varying mse and it can be observed that mse 1.0*e-06 has highest accuracy. Hence in this case the mean square error of the final neural network is chosen to be 1.0*e-06.

TABLE II MEAN SQUARE ERROR GOAL

Mean square error	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Correctly Classified Samples**	**Misclassified Samples**
1.0*e-01	93.1	89.6	9488	811
1.0*e-02	99.1	96.8	10141	158
1.0*e-03	100	96.5	10193	106
1.0*e-04	100	96.5	10196	103
1.0*e-05	100	96.5	10196	103
1.0*e-06	100	96.8	10205	94

C. Selection of Number of Neurons

Number of neurons used to design the proposed activity recognition method has been decided after training the network with various number of neurons. The neural network designed with neurons having highest training and testing accuracy is chosen as optimal. Table III shows the performance of networks varying number of neurons. It can be observed from Table III that 20-20-6 neuron network has highest accuracy. Hence number of neuron for the final neural network is chosen to be 20-20-6.

TABLE III SELECTION OF NEURONS

Number Neurons	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Correctly Classified Samples**	**Misclassified Samples**
5-5-6	100	96.7	10202	97
10-10-6	100	95.2	10158	141
20-20-6	100	96.8	10205	94
30-30-6	100	95.5	10166	133

D. Selection of Number of Hidden Layers

The proposed activity recognition method has been designed with optimal number of hidden layers. The optimal number of hidden layers has been decided after training the network with various number of hidden layers. The neural network with highest training and testing accuracy is chosen as optimal. Table IV shows the performance with varying number of neuron. It can be observed that two hidden layer has highest accuracy. Hence two hidden layers are chosen as optimal for final neural network.

TABLE IV SELECTION OF HIDDEN LAYERS

Number of Hidden Layers	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Correctly Classified Samples**	**Misclassified Samples**
1	100	95.6	10169	130
2	100	96.8	10205	94
3	100	96.6	10198	101

E. Selection Transfer Function

Transfer function used to design the proposed activity recognition method has been decided after training the network with various transfer functions such as purelin, log-sig and tan-sig. The neural network with transfer function having highest training and testing accuracy is chosen as optimal. Table V shows the performance of networks varying transfer function. It can be observed from Table V that tansig-tansig-purelin has highest accuracy. Hence it is chosen to design the final neural network.

TABLE V SELECTION OF TRANSFER FUNCTION

Transfer Function	**Training Accuracy (%)**	**Testing Accuracy (%)**	**Correctly Classified Samples**	**Misclassified Samples**
L-L-L	100	95	10151	148
L-L-P	100	95.2	10158	141
T-T-T	100	96.1	10184	115
T-T-P	100	96.8	10205	94

F. Overall Performance Analysis

Performance of the proposed method is also calculated using various parameters. Performance is evaluated for each of the six output classes separately. Table VI shows the performance of the training, testing and overall accuracy. From Table VI it can be observed that the training accuracy is 100% for all output classes. Testing accuracy is less in case of sitting class which ultimately reduces the overall testing accuracy. But the overall testing accuracy of the individual classes is above 97%. Hence the proposed method can be used effectively for human activity recognition.

TABLE VI PERFORMANCE OF INDIVIDUAL ACTIVITY

Output Classes	**Training Accuracy(%)**	**Testing Accuracy (%)**	**Overall Accuracy (%)**
Walking	100	99.4	99.826
Walking upstairs	100	98.5	99.546
Walking Downstairs	100	95.2	98.577
Sitting	100	89.6	97.129
Standing	100	97.6	99.317
Laying Down	100	100.0	100.00

V. CONCLUSION

This paper presents a PCA and ANN based method for human activity recognition from smart phone sensors. Input features given to the ANN based classifier is first analyzed with PCA. PCA analysis shows that total 381 features are required for classification. Testing accuracy of the proposed method is 96.8% in recognizing various human activity. The proposed method is very helpful in hospitals and homes for monitoring peoples.

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