Physical Activity Classification and Monitoring using Artificial Neural Network

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ABSTRACT
This paper provides an efficient way to design a physical activity classification and monitoring system using a wireless sensor network which consisting of cost sensitive tri-axial accelerometers. Physical activity increases the fitness level and exercise capacity of the human body and helps to reduce risk factors such as obesity, diabetes and extends the life expectancy. The main objective of this project is to develop a real-time and accurate physical activity monitoring system based on physical signal detection technique. To detect and classify multiple activities, the proposed system uses multi-sensor network which is able to overcome the limitations of a single accelerometer. It consists of an electronic device which is worn on the hip and finger of the person under test. The system can be used to monitor physiological parameters, such as temperature and physical activity of a human subject using temperature and accelerometer sensors. Artificial Neural Network is used to classifying the different physical activities such as jogging, cycling, normal and fast walking. Neural Network Toolbox in MATLAB is used to classify such kind of activities.

General Terms
Physiological parameters, Temperature, multi sensor network

Keywords
Accelerometer, Physical Activity, Artificial Neural Network.

1. INTRODUCTION
Real-time monitoring of human physical activity (PA) is important for assessing the intensity of activity and exposure to environmental pollutions. Today, the progress in science and technology offers miniaturization, speed, intelligence, sophistication, and new materials at lower cost, resulting in the development of various high-performance smart sensing system [1]. Many new research is focused at improving quality of human life in terms of health by designing and fabricating sensors which are either in direct contact with the human body (invasive) or indirectly (non-invasive).

One of the reasons for more development in this area is the global population and rise in ageing population, one statistic provided by the U.S. According to the data provided by U.S. Census Bureau, the U.S. population has shown steady growth since the year 1980 (0.8% - 1.2% annually) and is expected to reach 341 million by the year 2020. The life expectancy at birth has also shown a tendency to increase every year in the U.S because of advances in healthcare, medical research, sanitation, and nutrition. A U.S. child born in 2008 is expected to live four years longer than one who was born in 1981. It is expected that the U.S. population over age 65 will be more than 20% over the total U.S. population in year 2050 due to increasing life expectancy and decreasing birth rates. On the other hand, there is a declining trend in the number of hospitals in the United States due to the structural change in the medical industry. As a result, the cost of medical services has increased for patients and hospitals seek to reduce hospital admissions and the length of stay.

The number of hospitals in the U.S. dropped from 7,000 to 5,700 between the year 1975 and 2005. Nearly 20% of those in the US live in rural areas, but only 9% of physicians work in rural areas. This results in a requirement for medical care, which is expensive for long-term monitoring and long waiting lists for consultations with health professionals. The cost of hospitalization is ever increasing, so is the cost of rehabilitation after a major illness or surgery. Hospitals are looking at sending people back as soon as possible at home.

This technique offers non-invasive and low-cost measurement with low subject burden [3], [4], and studies [5] have shown effectiveness in using accelerometers for identifying PA intensities. However, using accelerometers alone has shown to be insufficient for distinguishing different types of activities. Furthermore, it does not quantify the human subject's exposure to environmental pollutions. To enable comprehensive and accurate assessment of PA intensity, type, energy expenditure and environmental exposure, multiple sensors are needed. Recent advancement in wireless technology has enabled increasing applications of wireless sensors for monitoring physical activities and human health [6]–[8]. Compared to wired systems, wireless sensors eliminate interference with activities caused by wire tangling, thus are more convenient to wear [9]-[11]. Accordingly, Wireless Body Sensor or area networks have quickly grown into a promising technology for human health monitoring.

2. OVERVIEW
2.1 Physical Activity Monitoring
Physical activity can be defined as "any body movement produced by skeletal muscles result in energy expenditure above resting level". Physical activity is important for people of every age and physical condition and should be an integrated module of human behavior in daily life.

In everyday life, mobile monitoring systems are needed to distinguish between basic activities types such as walking, jogging, running and cycling. The physical activity monitoring is based on the accelerometer (motion) sensor and temperature sensor. The motion sensors can be used to differentiate user activity states (e.g., sitting, walking, jogging and cycling), or estimate the intensity of activity. Depending on the target application, the activity sensor can be attached to the user's hip, an ankle, or the wrist.

More motion sensors can be deployed to achieve a more robust state differentiation and a better estimation of the user's activity. The temperature sensor measures the real time body temperature in degree Celsius and compares it with the normal human body temperature which is 37degree C.

2.2 Wireless Multi Sensor Measurement System

A wireless wearable multi-senor integrated measurement system (WIMS) has been designed for real-time measurement of the energy expenditure and breathing volume of human subjects under free-living conditions. The wireless sensors networks have become a great interest to research, scientific and technological community. Though sensor networks have been in place for more than a few decades now, the wireless domain has opened up a whole new application space of sensors. Wireless sensors and sensor networks are different from traditional wireless networks as well computer networks and, therefore, more challenges to solve such as limited energy, restricted life time, etc.

The WIMS collects data on body motion and temperature from the human subject. The data are subsequently extracted and fused to quantify the energy expenditure and determine the PA types through an embedded pattern recognition algorithm. Three sensors of two different types are included in the WIMS. The tri-axial accelerometers are worn at the hip and wrist, to measure the body and arm motions that characterize the degree of PA. One displacement sensor is wrapped around the wrist, for measuring the temperature. The corresponding temperature is monitored for different types of activities.

Newer accelerometer models are able to collect raw acceleration data for days or weeks at a time at very high sampling rates; accordingly, researchers have successfully used machine learning techniques, such as decision trees and artificial neural networks to identify PA type, as well as intensity. While machine learning algorithms developed from hip-mounted accelerometers can offer some ability to identify PA type and measure, obtaining information about movements of multiple parts of the body simultaneously can offer a greatly improved capacity for identifying PA type, intensity, frequency and duration. Each abdominal (AB) unit, wrist unit, and hip unit includes an 8-bit microcontroller (MSP430F149, Texas Instruments, Dallas, TX)) and a ZigBee module, enabling signal acquisition on-board and wireless data communication among the units.

3. PROPOSED TECHNIQUE

3.1 System Overview

To overcome the limitations of single tri-axial accelerometer based measures, the proposed system uses the physiological signal based on multi-sensor for activity monitoring.

The system consists of a wireless physiological signal-acquisition module and an embedded signal-processing module. First, the signal will be obtained by the accelerometer and temperature sensor, and then amplified and filtered by the amplifier and acquisition unit. Next, the signal will be pre-processed by the microprocessor unit and transmitted to the embedded signal processing module via a wireless transmission unit. After receiving the signal, it will be monitored and analyzed by classification algorithm implemented in an embedded signal-processing unit. If the abnormal state is detected, the warning device will be triggered.

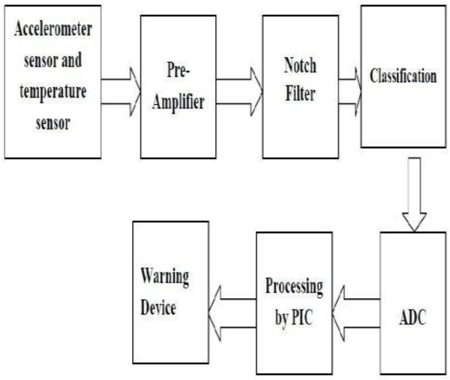

Fig 1: Block Diagram of the Proposed System

The acquisition unit includes an Instrumentation Amplifier, a Median filter for smoothing the signal, and an analog-to-digital converter (ADC), which is designed to amplify and filter the signals. The overall block diagram of the system is shown in the Figure1.Feature Extraction and Classification methods plays important role in Drowsiness detection system. For Feature Extraction the Auto Regression method is used. AR model is a representation of a type of random process it describes certain time-varying processes in nature and it specifies that the output variable depends linearly on its own previous values.

The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. The 12 bit ADC (Analog to Digital Converter) is used to give the digital output to the Microcontroller unit for decision making. The Instrumentation Amplifier will increase the SNR value because normally the signal from physical world having the low SNR value. The median filter with filter length of 3, and 1Hz low cut off frequency, 32 Hz high cut off frequency is used. The other method for feature extraction is Wavelet Decomposition. The frequency content of the signal provides useful information than time domain representation. The wavelet transform gives multi-resolution description of a non-stationary signal. Accelerometer and temperature is non-stationary signal.

3.2 Pre-processing of Signal

Pre-processing includes the pre-amplification and filtering of signal. The amplification module is required to amplify the small potential from accelerometer and temperature sensor to the acceptable level. The pre-amplifier should include the signal conditioning circuit which has the filtering circuit.

3.3 Microcontroller Circuit

Microcontroller is a standalone unit, which can perform functions on its own without any requirement for additional hard ware like I/O ports and external memory. It is also called as ‘computer on chip’. Microcontrollers are destined to play an increasingly important role in revolutionizing various industries and influencing our day to day life more strongly than one can imagine. By using the extracted signal the microcontroller make decision on the input signal i.e. whether the incoming signal is in abnormal state or not.

3.4 Classification Algorithm

Classification can be divided into two categories: analytical models and machine learning methods. Analytical models, such as decision tree, decision tables and neural network are usually threshold based techniques. The advantage of such classifiers is less required calculation power; however, since the thresholds are usually fixed values, the performance of classification varies from subject to subject.

3.5 Neural Network based Classification

Artificial neural networks are biologically inspired classification algorithms that consist of an input layer of nodes, one or more hidden layers and an output layer. Each node in a layer has one corresponding node in the next layer, thus creating the stacking effect. Artificial neural networks are the very versatile tools and have been widely used to tackle many issues.

Feed-Forward Neural Network (FNN) is one of the popular structures among artificial neural networks. It consists of a (possibly large) number of simple neuron-like processing units, organized in layers. Every unit in a layer is connected with all the units in the previous layer. The Levenberg-Marquardt Algorithm can be used to train the neural network. This algorithm is accurate and take less time when compare to Bayesian Regularisation algorithm.

4. SIMULATION

4.1 Introduction to EDF Browser

EDF browser is a free, open source, multi-platform, universal viewer and toolbox intended for time series storage files like SKT, Bio-Impedance etc. Using EDF browser, the numerical values of temperature and position can be obtained from its corresponding graphical representation. Hence, the different datasets are created by using these values. The simulation is done in MATLAB 2014a.

4.2 Systems involved in Simulation of the System

The simulation part consists of the following steps:
The input signals are taken from the accelerometer sensor.
The accelerometer signals are filtered and wavelet decomposition is performed to classify the signal.
The features such as mean, entropy, variance and kurtosis are determined.
Based on the extracted features, the signals are classified and the corresponding temperature is monitored for different types of activities.

4.3 Result Analysis

Figure 2 indicates the accelerometer signal under the condition when no action is performed by person. The EDF browser does not provide the data for no action is performed. This accelerometer signal is of the duration of 100 ms.

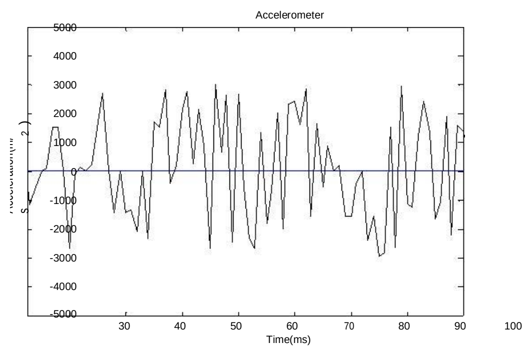

Fig 2: Observed Accelerometer Signal

4.4 Result of Wavelet Decomposition

The output of the accelerometer sensor is subjected to Wavelet Decomposition. A wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. By using Wavelet Decomposition, the components of accelerometer signal are separated.

Table 1. Database

Time(ms)	Acceleration(m/s^2)
0	1887.6173
0.01781	235.6145
0.0717	236.8047
0.09562	287.0457
0.11953	304.7379
0.52343	1694.254
0.03120	-1789.230

Table 1 describes the database for accelerometer signal. Figure 3 shows the accelerometer output for an activity. Initially, a value from the database must be given as input to the system .Based on the extracted feature of the input; the corresponding activity signal will be given as output.

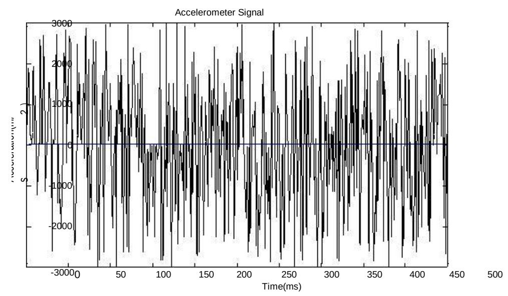

Fig 3: Accelerometer Signal

A notch filter is mainly used to reduce the noise from the accelerometer signal. It is also a band-stop filter with a narrow stop band. The band-stop filter or band-rejection filter is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels.

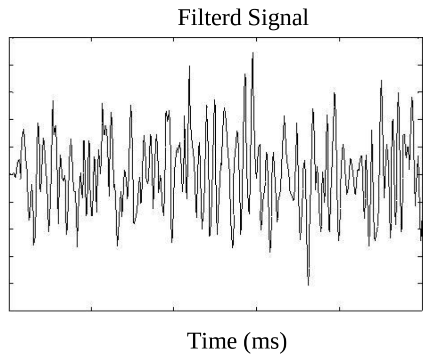

Fig 4: Filtered Signal

The different input signals are classified based on feature extraction with features such as entropy, kurtosis, mean and variance. Entropy is a statistical measure of randomness that can be used to characterize the input data. Entropy is defined in Equation 1 where p denotes the probability density.

Entropy=-sum p*$\log_2$ p (1)

function is most commo nly associated

A probability
density ?( )?

with continuous random variable. A random variable X has density fx, where fX is a non-negative function.

b

Probability density= fx x dx (2)

a

of t he
peakedness probability

Kurtosis is a measure of the ∫ ( )

distribution of a real-valued random variable. T he kurtosis is defined as

? = (????µ) (3)

Where µ is the mean of X, σ is the standard deviation of X, and E (t) represents the expected value of t he quantity t. Kurtosis computes a sample version of this population value.

Mean refers to the measure of the central tende ncy either of a probability distribution or of the random variable characterized by that distribution. Mean returns the sum of the value along the first array dimension of A whose size does not equal 1.

$$\text{Mean} = \frac{\text{sum of the variable}}{\text{Total number of the variable}} \quad (4)$$

Variance is the measure how far a set of numbers is spread out. A variance of zero indicates that all t he values are identical. Variance is always non-negative a s mall, variance indicates that data points and hence, a high variance indicates that the data points are very spread out around the mean and from each(other).

VAR X, 1 =SUM(RESID.*CONJ(RESID))/N (5)

Where RESID = X – MEAN(X) and N is length of X.

Table 2. Feature Extraction

Activity	Mean	Variance	Kurtosis	Entropy
Jogging	812.2	48718.705	3.07321	1.01080
Normal Walk	146.8	94230.726	1.04235	1.00068
Fast Walk	527.5	20255.850	1.03986	1.00067
Cycling	375.2	8932.4945	3.33857	0.07740

Fig 5: Output Message

Based on the input data, the parameters like mean, variance, kurtosis and entropy are calculated using mathematical formula. The calculated values are shown in Table 2 which is used to characterize the signal. From these valu s, the input isidentified by the system and the ou tput message will be displayed as shown in Figure 5.4.

4.5 Performance Analysis

The classification of various input signals can be done by using neural network. The feed forwa rd network is used to train the system. In feed forward neural network, the information moves in only one direction, forward, from the input nodes, through the hidden nod es (if any) and to the output nodes. There are no cycles or feedback loops in the network.

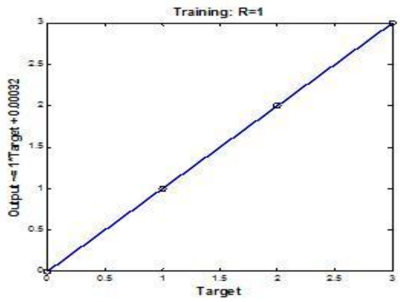

Fig 6: Regression Plot

Figure 6 shows the regression plot which is a statistical process for estimating the relationships among different activities. Figure 7 shows the Best Training performance plot. It shows the change in mean square er ror with respect to the number of epochs.

Fig 7 Performance Plot

It can be seen from the figure that the mean square error reduces as the number of epoch's increases. Hence the system will have improved performance at l ow mean square error. Figure 8 shows the training state plot.

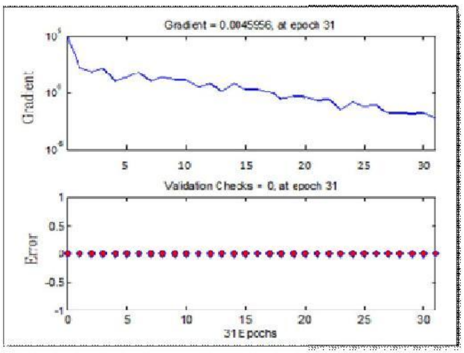

Fig 8: Training State Plots

Table .3. Neural Network Design and Specifications

S. No	Parameters	Value
1	Type of Network	Feed-Forward
2	No. Of Neurons in the hidden layer	15
3	Performance function	MSE
4	Training function	Levenberg-Marquardt
5	Activation function in the hidden layer	Tan-Sigmoid
6	Activation function in the output layer	Linear
7	Maximum no. of epochs	50

The Network design and specification is given in Table 3. Based on the specification, the Feed Forward neural network is trained.

5. COMPARISON WITH EXISTING METHOD

Comparison of the proposed system with existing system is showing in Table 4...The Existing system uses the Low pass filter. Bayesian Regularisation algorithm takes the mean square error as 0.0001and the Levenberg-Marquardt algorithm takes the mean square error as 0.000001. When compared to the two algorithms the Levenberg-Marquardt algorithm can give the effective mean square error. This algorithm typically takes more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean-square error of the valuation samples.

Table4. Comparison with Existing Method

S. No	Parameter Used	Existing Method	Proposed Method
1.	Pre-processing	Low pass filter	Notch filter
2.	Algorithm	Bayesian Regularization	Levenberg-Marquardt
3.	Mean Square Error	10^{-4}	10^{-6}

6. CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In this project various physical activities of a human being are identified using accelerometer and temperature sensor and it also detects the human's abnormal condition. The system takes the inputs from accelerometer sensor and temperature sensor. Based on these inputs, physical activities are classified using the artificial neural network. The accelerometer is used to provide the present activity of the person and the corresponding temperature can be measured using temperature sensor. The activity and physical status of the person is simulated using MATLAB coding and the results indicate the different movements of the person. When compared to existing system, the physiological signal measure is portable, wearable and has high temporal resolution.

6.2 Future Scope

The future scope of this work is to implement the intelligent system which classifies the human physical activity based on the inputs from the accelerometer and temperature sensors. The system will also use the Zig-bee protocol to transmit the identified state of the person under consideration to the remote receiver.

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