Real-Time Processing and Analysis for Activity Classification to Enhance Wearable Wireless ECG

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Real-time Processing and Analysis for Activity Classification to Enhance Wearable Wireless ECG

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Abstract. Health care facilities of our rural India are in a state of utter indigence. Over three-fifths of those who live in rural areas have to travel more than 5 km to reach a hospital and the health care services is becoming out of reach for the economically backward society of India. Currently, as the rural community experiences about 22.9% of death due to heart diseases [1], there is a need to improve the remote ECG monitoring devices to cater the needs of rural India. The existing wearable ECG devices experience several issues to accurately detect the type of heart diseases due to the presence of motion artifacts, and to warn the doctor during critical conditions. Hence, even though wearable devices are finding their place in today's healthcare systems, the above mentioned issues discourages a doctor in depending upon it. So to enhance the existing wearable ECG device, a context aware system was designed to collect the BMA (Body Movement Activity). In this research work an innovative BMA classifier has been designed to classify the physical activities of users, from the real-time data received from context aware device. The test results of the BMA classifier integrated with the complete system shows that algorithm developed in this work is capable of classifying the user activity such as walking, jogging, sitting, standing, upstairs, downstairs, and lying down, with an accuracy of 96.66%.

Keywords: BMA (Body Movement Activity), BMA classifier, motion artifacts, Context aware.

1 Introduction

Health care in rural India is 1.5 times more expensive than urban areas [2]. Every year, approximately 20 million people are pushed below poverty line due to the health expenditure alone. Wearable health care devices can be used to deliver low cost and efficient health care service facility.

A comparison of mortality rate for major diseases is shown in Fig.1. According to the World Health Organization, heart related disorders will kill almost 20 million people by 2015 [4]. However there are no existing low cost systems that would help us to identify the reason for the abnormalities in heart functions. As cardiovascular diseases are one of the most common diseases in rural India, it is crucial to integrate preventive measures or provide early warnings about such diseases. This necessitates continuous monitoring of the patients ECG to provide appropriate medical advices in real-time to the patients in the rural village.

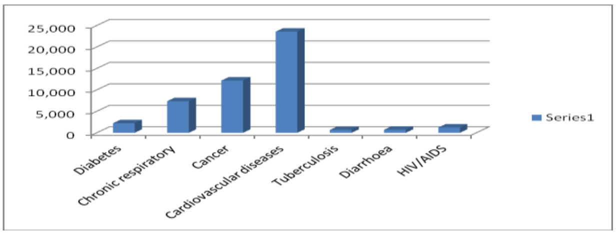

Fig.1 mortality from major communicable and non-communicable diseases, 2030 [3]

With the development of wireless sensor networks and embedded system technologies, miniaturized wearable health monitoring equipment has become practically realistic. This can help in remotely monitoring a patient's health status. Since, cardiac diseases are one of the major concerns in rural India, systems for detecting cardiac diseases is highly necessary. One of the methods for detecting cardiac diseases is achieved through ECG signal analysis**.** ECG is used to monitoring heart's rhythm and it generates a waveform by picking up electrical impulses from the polarization and depolarization of cardiac tissues. This waveform is widely adopted to diagnose and assess major health risks and chronic cardiac disease. This project deals with improving the quality of the data received from a remote wearable ECG device attached to the body of the patient which can aid the doctor in diagnosing the patient properly. Accurate interpretation of the electrocardiogram requires high quality signals that are free from distortion and artifact. But motion and noise artifacts arising from a biological origin, like reciprocal contamination of muscle activity and heart cycles or environmental, experimental and physiological factors will affect the degradation of ECG signal quality. Artifacts causes significant problems as it affects the display information during surgery and it also makes early detection and warning of imminent heart related diseases difficult. Another problem faced is the inaccurate information recorded in automated systems which have become a source of false alarms. So to improve the quality of the ECG, the physical movement of the patient should also be monitored simultaneously, compared and classified.

The motion artifact in ECG is related to the Body Movement Activity (BMA). BMA can be collected effectively using accelerometer. Accelerometer signals can be used as the reference signal to identify the type of movement, which can be further used for filtering out the motion artifacts. It is one of the best methods to identify patient activity it is proportional to external forces and hence can reflect the intensity and frequency of human movement. This work focuses on design of a context aware system, integrated with an efficient BMA classifier algorithm to detect patients movement, and to classify them in real-time. In future, these results can be used to remove the motion artifacts in the ECG signals.

Section II describes about the related works. Design of context aware system is presented in section III. Section IV discuss about feature extraction of accelerometer data. Section V describes implementation and testing of the system. And finally VI gives the conclusion of the work.

2 Related works

Challenges faced with existing schemes are small amplitude, narrow width, and varying wave shaped makes artifacts which are very difficult to detect, especially in the presence of electrical noise. Due to the pulse variation caused by BMA there are chances for misinterpretation of ECG data (disease like arrhythmia). The existing systems have many issues like high power consumption, less memory availability, and high computational cost. This paper discusses about the design of real time cardiac monitoring without restricting patients activity.

Jennifer R. Kwapisz et.al conducted a detailed analysis of activity recognition using available accelerometer data base [5]. Nearly, data from 29 users performing daily activities like walking, jogging, climbing stairs, sitting and standing were collected, for implementing the system. The aggregated data was controlled using mobile phone application. The paper shows only the simulation result related to the available data base. The limitation of this system is that the activity recognition results are generated off-line and are not reported back to the mobile phone and the user.

Tanma Pawar et.al proposes a technique to identify the motion artifacts and classify the specific type of activities from the ECG signal [6]. Two different types of uncorrelated BMA are used to find motion artifacts. A particular class of BMA is classified by applying Eigen decomposition in the corresponding ECG data. When stair climbing was tested using their system it was accurate but there was confusion when testing walking, climbing down stairs and movement of left, right or both arms. The proposed method here uses accelerometer data with computationally less intensive statistical classifiers for detecting the MIA (Motion Induced Artifacts). The cost of power for computations when the device is in continuous monitoring mode has to be kept at a minimum.

Annapuma Sharma et.al conducted a detailed analysis of frequency based classification of activities such as Rest, Walk and Run, using accelerometer data [7]. This paper highlights the classification of user activities based on frequency components seen in the accelerometer readings in a wireless sensor network. The data collection can be done in the order of REST-WALK-RUN and the classifier is developed only for these activities. The main limitation of this system is that the test was conducted placing the sensor unit only on chest. And the system is tested using only single hop communication, not for multi-hop communication.

Davide Figo et.al conducted a detailed analysis of context recognition from accelerometer data by using preprocessing techniques [9]. The approaches used the main signal processing techniques are time domain, frequency domain and discrete representation domains. Each domain has its own specific method to abstract raw signal data, in addition early classification and some data compression techniques that it makes to possible use in context recognition were discussed. Frequency domain techniques are better as the computational cost of computing frequency spectrum either using FFT method or wavelet is less.

3 Design of context aware system

An existing wearable ECG device that can be worn as a belt around the patient's waist is used for performing our research to enhance the accuracy and effectiveness of the ECG system. The wearable ECG device will be enhanced so that the device will be capable to collect the ECG and accelerometer data of the patient and send it via Bluetooth to the patient's smart phone.

Using the BMA classifier algorithm and artifact detection method, an initial level filtering of ECG data will be performed in real-time, to remove the artifacts. The warnings based on the clean data will be send to doctor for diagnosis and future analysis, using the cellular network. As the first phase of this work, we have designed a context aware system for classifying BMA.

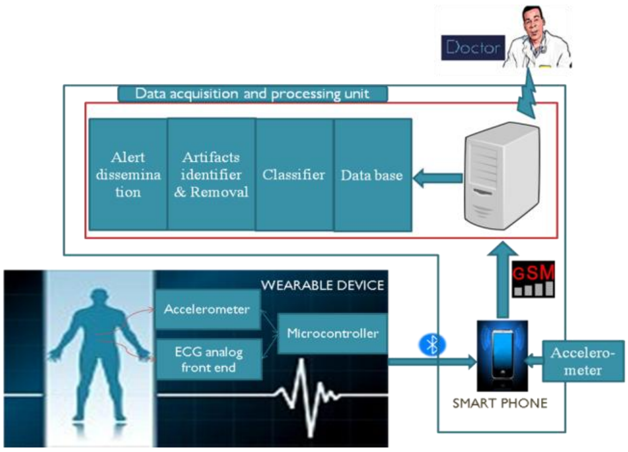

Fig. 2 Overall system architecture

The objective of the proposed system is to collect real-time ECG data along with the accelerometer data due to body movements. The system will classify the real-time accelerometer data as different activities related to body movements, and use those results to identify the motion artifacts in the ECG data. The overall architecture of this system is shown in Fig.2. The major modules of the systems are wearable device, mobile phone integrated with accelerometer, and data acquisition and processing unit. The details are given below:

3.1 Wearable device

It consists of a wearable sensor unit which is used to gather real time data from users. The heart of the wearable unit has an ECG analog front end single chip system for ECG, ADS1292 from Texas Instruments, MSP430 micro-controller and to monitor the connection between skin and electrode, which has the ability to monitor physical activities in low power mode. Bluetooth 2.0 connectivity is used for transmitting data to a smart phone or to a compatible wireless device.

The data from the wearable device is send via Bluetooth to the patient's smart phone. An android application is implemented on the smart phone which uses the Bluetooth SPP (serial port profile) to connect with the wearable ECG device. The smart phone uses GSM network to send the data received from the wearable device to the remote data server (RMD).

3.2 Data acquisition and processing unit

The data acquisition and processing unit consists of a database, classifier, artifact identifier, alert dissemination etc. Data acquisition unit receive the data and store into database. A BMA classifier algorithm runs on the back end server for classifying the user's activities. The classifier combines different processing techniques in an optimal way to classify the BMA accurately. The result will be shown in the visualization unit. Further extension to the system is provided by simultaneously analyzing the accelerometer data and then using it to predict and filter out the motion artifact present in the ECG data.

4 Feature extraction from accelerometer data

4.1 Orientation of accelerometer

In this system a triple axis accelerometer ADXL345 with a measurement range of +/-2g is used for activity monitoring. The placement of accelerometer is shown in *Fig.3.* When the person is standing (ideal case) , the x-axis output is 0g, y-axis output 1g and z-axis output 0g . An initial level classification can be done for the basic activities like sitting, standing and lying down from the orientation of the accelerometer. Also, major changes in the data will be observed in the Y-axis during dynamic body movements.

Fig.3 Orientation of accelerometer in wearable device

4.2 Preprocessing techniques

There are both time domain and frequency domain based pre-processing techniques. Time domain preprocessing techniques are mean, average, root mean square value, min/max, range and variance. Frequency domain approach includes as FFT (Fourier Frequency Transform) and dominant frequency. Simple mathematical and statistical methods can be used to extract basic information from accelerometer data. Using these methods for preprocessing can help selecting key signal characteristics. The details of various preprocessing techniques are given below:

1) Min/Max: Returns smallest and largest magnitude. This classifier could be used to short duration study body movements.
2) Range: Provides the difference between the largest and smallest values. This information can be used to find out the dynamicity in the data, which can help in discriminating similar activities like walking, running and jogging.
3) Mode: Retrieves the value that occurs most often. This is relevant only if the data is repetitive.
4) Median: Provides the middle value in the list of numbers. It is used to identify different inclination angles while walking, as well as to distinguish between types of postures with threshold-based techniques.
5) Mean: Provides the average value. It requires low computational cost and is done with minimal memory requirement. It is used to process accelerometer data with random spikes and noise.
6) RMS: It gives a statistical measure of the magnitude of a varying quantity. It is used to distinguishing walking patterns.
7) Variance: Defined as the average of the squared differences from the mean. This classifier is used to identify the signal stability.
8) Dominant frequency: Used to find maximum frequency component in the signal.

Frequency-domain techniques have been extensively used to capture the repetitive nature of accelerometer signal Frequency-domain techniques seem to provide both fairly good accuracy and also fairly good consistency.

5 Feature extraction from accelerometer data

5.1 BMA classifier implementation

A classifier has been designed for classifying seven activities such as lying down, walking, jogging, standing, sitting, upstairs and downstairs. The accuracy of the classifier was tested in two stages. An initial framework of the classifier was designed using an existing database. The database included data collected from 29 users performing daily activities like walking; jogging, climbing stairs, sitting and standing. Based on the test observation various thresholds and decisions were set to increase the efficiency of the classifier. The second test was conducted on real data collected from

5 users (both male and female) ranging in ages (20-25). The accelerometer was placed on hand, pocket and belt position. A total of 105 samples of accelerometer data for duration of 30 sec, was collected at 100 samples/sec while the user was performing daily activities like jogging, walking, standing, upstairs, downstairs, lying down and sitting. As the wearable device accelerometer was under test stage, a Smart phone based accelerometer kept in the same orientation was used as a substitute the test the classifier. The accelerometer was oriented in way that the x-axis gives the horizontal movements, y-axis value represents the up and down movements, and the value of z-axis represents the body forward movement shown in Fig.4.

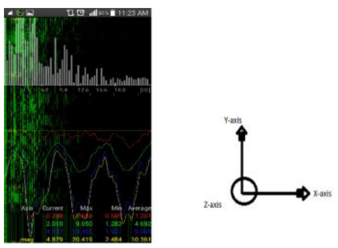

Fig. 4 Jogging activity occurs in y-axis

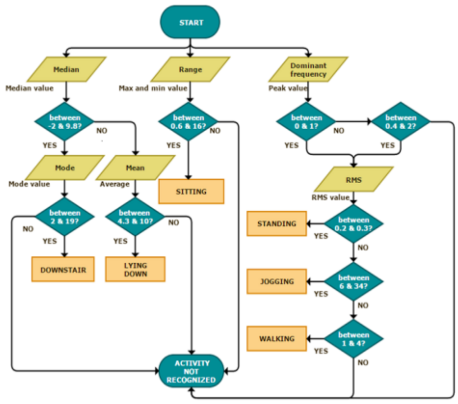

Fig. 5 Flowchart of BMA algorithm running in the MATLAB

The flowchart of the proposed BMA classifier algorithm is shown in Fig.5. Threshold based approach is used here for classification of user activity. The classifier checks whether it is jogging or standing. If the activity is not jogging or standing it is go the start stage otherwise it is go the RMS classifier algorithm. In the output of the RMS classifier is not jogging / standing it check the activity is walking. In the range classifier take the input signal and check it is sitting. If the activity is not sitting it is go to the end stage. The RMS and Median classifier collect the signal from input. The median classifier check the activity is downstairs or not if yes it goes to the mode classifier. If it is not downstairs it goes to the mean classifier check it is lying down otherwise the graph is end. The collected data can be fed into the data acquisition and processing unit that contains the BMA classifier algorithm running on MATLAB. Different classifiers are implemented in the MATLAB. Based on the multiple classifiers the real-time data from mobile phone is classified.

5.2 Testing and results

The results of the above tests are given below. When the patient is doing activities like walking or jogging there is a random nature shown in the x-axis (red), y-axis (green) and z-axis(blue)(Fig. 6. and Fig. 8). In the case of jogging there is relatively high acceleration seen in the y-axis. Frequency-domain techniques have been extensively used to capture the periodic nature of accelerometer signal. It is used to detect the repetitive nature of a specific activity such as walking or running. The two movements can be distinguished with dominant frequency classifier, RMS and mean classifier. The magnitude of x, y and z-axes values are used to distinguish between lying down and standing activity because there was no periodic pattern. Walking activity in this experiment is normally walking with an average speed of 4.5km/h. Jogging is normal jogging with an average speed of 5km/h. All the experiment was done with the help of triple-axial accelerometer at different positions. In the case of jogging and walking and jogging there is a periodic nature shown in Fig. 7 and Fig. 8. In the case of standing and lying down activity it is similar to each other is shown in Fig. 10 and Fig. 11. The difference will be only in the orientation of accelerometer which can be obtained from the g-force. In the case of sitting activity gap between x, z and y –axis data is large but standing the gap is less shown in Fig. 11 and Fig. 12. The plot of accelerometer data for different activities is shown in Fig.6 to Fig.14.

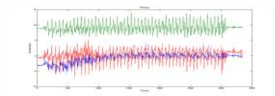

Fig.6 Walking

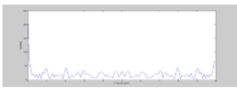

Fig. 7 Walking (FFT)

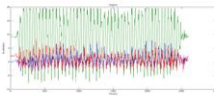

Fig. 8 Jogging

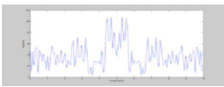

Fig.9 Jogging (FFT)

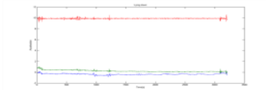

Fig. 10 Lying down

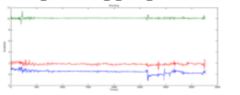

Fig.11 Standing

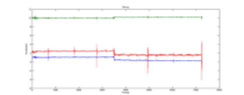

Fig.12 Sitting

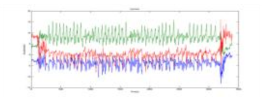

Fig.13 Upstairs

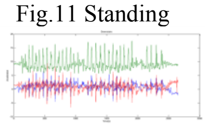

Fig.14 Downstairs

The above results show that in the case of standing and jogging dominant frequency showed 100% accuracy while variance and RMS showed 86.66%. In the case of walking, RMS showed 93.33% accuracy and for downstairs median showed gave 100% accuracy. In the case of sitting, range gave 93.33% accuracy. And in the lying down RMS technique showed 100% accuracy. In the case of upstairs 86.6% accuracy was obtained using dominant frequency technique. The performance of the developed classifier was analyzed by using confusion matrices TABLE (I to XI).

TABLE I. Lying down activity

X	Y	Z
-0.3521	0.2375	9.8889
-0.4295	-0.4997	9.9159
1.4263	0.483	9.9766
1.1668	1.0559	9.9877
0.5994	0.7897	9.9877

TABLE II. Dominant frequency classifier

	ST	JO	WA	SI	UP	DW	LY
ST	15	0	0	0	0	0	0
JO	0	15	0	0	0	0	0
WA	0	1	9	0	5	0	0
SI	11	0	0	3	0	0	0
UP	0	1	0	0	12	2	0
DW	0	2	1	0	8	4	0
LY	12	0	0	0	0	0	3

TABLE III. Minimum classifier

	ST	JO	WA	SI	UP	DW	LY
ST	7	0	0	3	0	5	0
JO	0	13	1	0	0	1	0
WA	0	5	9	0	1	0	0
SI	11	0	0	1	0	0	0
UP	0	5	7	0	2	0	0
DW	0	4	7	0	2	1	0
LY	1	0	0	0	1	0	13

TABLE IV. Maximum classifier

	ST	JO	WA	SI	UP	DW	LY
ST	10	0	0	1	1	0	0
JO	0	4	0	0	0	0	0
WA	0	11	3	0	1	0	0
SI	14	0	0	0	0	0	0
UP	0	10	2	0	1	1	0
DW	0	10	3	0	0	0	0
LY	0	1	0	0	0	0	12

TABLE V. Mean classifier

	ST	JO	WA	SI	UP	DW	LY
ST	13	1	0	0	0	0	0
JO	2	13	0	0	0	0	0
WA	0	14	1	0	0	0	0
SI	11	1	0	1	0	0	0
UP	5	7	1	0	2	0	0
DW	6	4	0	0	1	0	0
LY	0	0	0	0	0	0	15

TABLE VI. Average mean classifier

	ST	JO	WA	SI	UP	DW	LY
ST	12	0	0	0	0	0	2
JO	2	10	1	0	1	0	0
WA	6	6	2	0	0	0	1
SI	14	1	0	0	0	0	0
UP	7	5	0	0	2	0	1
DW	8	6	0	0	0	1	0
LY	1	11	0	0	1	0	1

TABLE VII. Mode classifier

	ST	JO	WA	SI	UP	DW	LY
ST	0	0	1	0	0	13	0
JO	0	2	0	0	0	3	0
WA	1	1	1	0	0	5	1
SI	0	1	1	0	0	13	0
UP	0	4	1	0	0	11	0
DW	1	1	1	0	0	12	0
LY	0	0	6	0	1	0	7

TABLE VIII. Median classifier

	ST	JO	WA	SI	UP	DW	LY
ST	7	1	0	0	0	5	0
JO	0	4	1	0	0	4	0
WA	0	5	2	0	0	3	1
SI	2	0	0	0	0	12	0
UP	0	3	0	0	1	11	0
DW	1	0	0	0	0	14	0
LY	0	0	0	0	0	0	15

TABLE IX. RMS classifier

	ST	JO	WA	SI	UP	DW	LY
ST	13	0	1	0	0	0	0
JO	0	13	0	0	0	0	0
WA	0	0	14	0	0	0	0
SI	12	0	0	0	0	0	1
UP	0	0	14	0	1	0	0
DW	0	3	8	0	3	0	0
LY	12	0	2	0	0	0	0

TABLE X. Variance classifier

	ST	JO	WA	SI	UP	DW	LY
ST	5	0	0	10	0	0	0
JO	0	11	0	0	0	1	0
WA	0	13	1	0	0	0	0
SI	0	0	1	14	0	0	0
UP	0	13	0	0	1	1	0
DW	0	12	0	0	1	0	0
LY	2	0	4	0	8	0	1

TABLE XI. Proposed BMA classifier confusion matrix

	ST	JO	WA	SI	UP	DW	LY
ST	15	0	0	0	0	0	0
JO	0	15	0	0	0	0	0
WA	0	0	14	0	1	0	0
SI	0	0	0	14	0	1	0
UP	0	1	1	0	13	0	0
DW	0	0	0	0	0	15	0
LY	0	0	0	0	0	0	15

The proposed BMA (Body Movement Activity) classifier algorithm showed that in the case of standing and jogging dominant frequency showed 100% accuracy and the RMS and mean showed 93.33% accuracy. In the case of walking, RMS showed the 93.33% accuracy and for downstairs, median showed 100% accuracy. In the case of sitting range classifier shows 93.33% accuracy. And while lying down, mean and median showed 100% accuracy. In the case of upstairs dominant frequency showed 86.6% accuracy. The above result showed that the overall accuracy of classifier is 96.66%.

6. Conclusion and future work

In this paper, we have presented the study of various preprocessing techniques for classifying BMA and developed an initial framework of a classifier algorithm for classifying patient BMA. Both time and frequency domain based pre-processing techniques are used for improving the accuracy of the classifier. The result showed that the developed classifier was capable of classifying user activity with an accuracy of 96.66%. The frequency domain technique which classified the data more accurately was used as the base of the developed classifier algorithm, to achieve this level. Based on the analysis hip was found to be the best to place a triple-axial accelerometer for detecting activities. The future goal is to enhance the efficiency of the classifier and to incorporate real time dynamic filtering to deliver an artifact free ECG signal for diagnostic purpose.

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