Classification of Human Movement based on Radio Signals in Wireless Body Area Network using Artificial Neural Networks

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ABSTRACT

This paper aims to classify the signals acquired using wireless sensors placed on Human body for various human activities such as running, walking and standing. The proposed method can identify the three human movements using the radio signals transmitted using wireless sensors. Open NICTA provides the BAN (Body Area Network) measurement channel in three kinds of human motions. This paper used all nine sets of the measurement data for each human activity with respect to transmitter-receiver from back chest, right wrist - chest, right ankle - chest, chest - right hip, right wrist - right hip, left wrist - right hip, right ankle - right hip, left ankle - right hip and back - right hip. All the dataset was separately processed for individual human activity and then the features were combined for training the classifier. The feature set comprised of 11 components along the second dimension of each signal with a window of 25 samples thus reducing the samples to 160 from 4000. Only 27 front line features were considered form 99 to reduce the dimensionality while securing accuracy. The selection of only 27 features was settled after inspection about the deviation of each sample from the mean. The system achieved an accuracy of almost 99% using Artificial Neural Networks for the test samples which was 25% of the total dataset. The cross validation showed an average accuracy of 99%.

KEYWORDS - *Wireless sensors, radio signals, Open NICTA, BAN, human activity, Artificial Neural Networks.*

Article Received: 10 August 2020, Revised: 25 October 2020, Accepted: 18 November 2020

INTRODUCTION

In recent years, very interesting researches are concentrated to develop patient monitoring systems for revolutionizing health monitoring. Therefore, WSN had gained immense concentration and most of the researchers are working on optimizing its various parameters. Wireless body area network (WBAN) has been recognized as one of the promising wireless sensor technologies for improving healthcare service, thanks to its capability of seamlessly and continuously exchanging medical information in real time [4]. Biomedical applications of body area networks (BANs) are evolving, where taking periodic medical readings of patients via means wireless technologies at home or in the office will aid physicians to periodically supervise the patient's medical status without having to see the patient. Thus, one important objective of BANs is to provide the doctor with the medical readings that can be collected electronically without being in close proximity to the patient. The measurement of the patient's physiological signals via means of wearable sensors, believed to provide patients with easy healthcare for continuous health monitoring.

Body area networks had gained wide popularity in the field of medical applications due to its capability to measure different physiological values from various parts of human body. They are considered to be heterogeno us sensor networks [1]. As an example, a power and area efficient electrocardiogram (ECG) signal processing application specific integrated circuits (ASIC) for wireless body area networks (WBAN) is proposed in [2] where the ASIC can accurately detect the QRS peak with high frequency noise suppression occupying just 1.2 square mm area and consuming 9 microwatts. For medical applications, WBAN should collect and transmit information of patient in a reliable manner and in a timely manner to monitoring entity [3]. More sophisticated work on BAN can be found on [5-6].Most of the population in countries like India belongs to the rural areas where medical facilities are not sufficient and reachable. Also, the number of adults with chronic diseases fail to reach the medical care available in cities due to economic conditions. However, the advancement in wireless sensor networks have reduced the medical cost and its communication could bridge the gap between the care providers and the patients. The medical care had been affordable and accessible these days.

Wireless Body Area Network (WBAN) is a network of tiny sensors attached on human body or immersed inside the human body from where the data is being required for analysis. The usage of BAN system is now used in every field of medical and engineering [7], [8]. Today almost 70-80 percent of the elderly population in India is affected with Arthritis, spondylitis, spondylosis and other physical problems. The physiotherapist would certainly suggest few fitness exercises. It is not feasible for the patient to remain admitted at the health care center for long time. In such cases, information about human activities is helpful for self-awareness tools and/or used as a medical profile. Thus, monitoring the patient activities from far end becomes necessary to properly treat the patient. The communication in WBAN could be improved when the propagation channel propertiesare known. The performance of BAN can be optimized in terms of power consumption, as well as communication reliability, by using the information of propagation channel status [9], [10]. An accelerometer is widely used to monitor the human activities but it has some limitations. The accelerometer is not able to detect slow movement of the human activities such as sitting idle or just standing still [11-13]. Although the accelerometer well classifies dynamic human activities such as walking or running. Therefore, the proximity between body segment estimated by Radio Signal Strength Indication (RSSI) value could be used. The combination of accelerometer and RSSI in the human posture identification was investigated in [14]. The activity classification using empirical RF propagation modeling and inertial sensor in BAN was also investigated in [15]. However, this paper uses the dataset based on the radio signals acquired from 9 sensors over the human body without the use of accelerometer.

The primary objectives of this study are to utilize WBAN technology effectively for transmissions and receptions of signals from human body under various movements, acquire radio signals from various sensors place at wrist, ankle and chest, develop reliable and practical human motion identification system and accurately classify human movements. OpenNicta had provided the data of human movements using WBAN. The details are provided in the subsequent sections thus covering the first two objectives of the proposed work. The remaining two objectives are achieved using the following system presented in the proposed system section.

THE PROPOSED SYSTEM

The block diagram in figure 1 below shows the proposed system where the first stage involves arranging the vectors properly as per requirement from the available structure element of the data source.

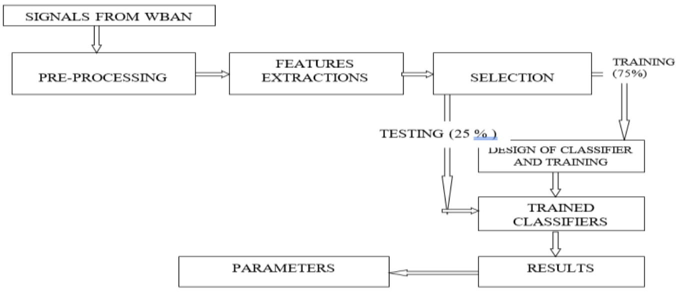

Figure 1 – The proposed system for classification of human activities based on radio signals using wireless sensors over the human body.

Each sensor with its reference sensor reads 4000 samples. Thus 9 such rows corresponding to 9 sensors are arranged in a vector matrix resulting in 9x4000 vector. The different wireless sensor combination used on the human body are:

1. back chest,
2. right wrist - chest,
3. right ankle - chest,
4. chest - right hip,
5. right wrist - right hip,
6. left wrist - right hip,
7. right ankle - right hip,
8. left ankle - right hip and
9. back - right hip

The following figure 2 shows the three activities over first three sensors viz back chest, right wrist – chest and right ankle – chest.

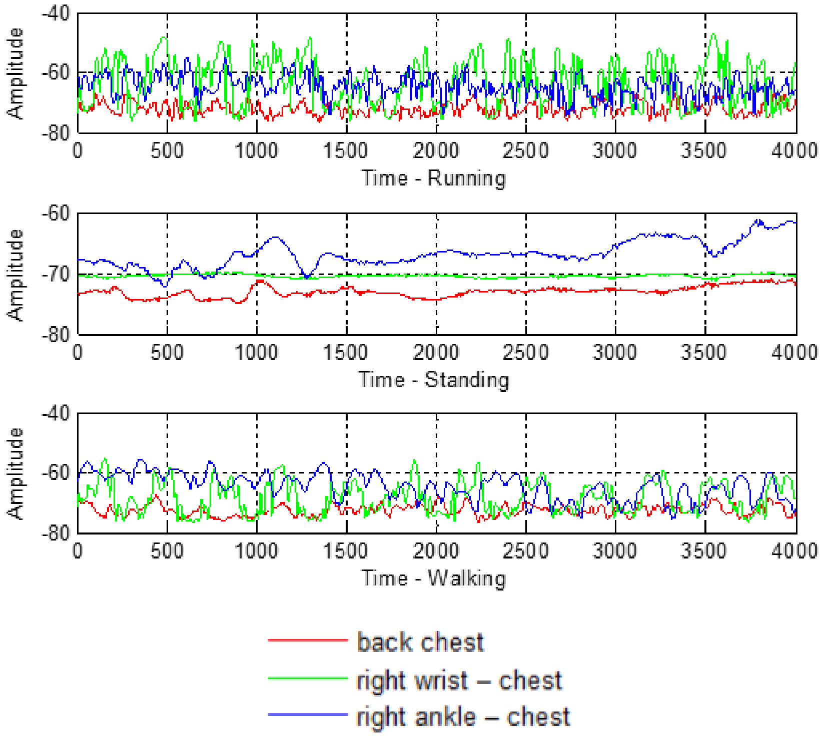

Figure 2 – Radio signals from three sensor back chest, right wrist – chest and right ankle – chest for all three human activities: Running, Walking and Standing

The dataset contains three human activities:

1. Running
2. Walking and
3. Standing

Thus, three vectors with size 9x4000 are acquired and stored in vectors R, W and S respectively for running, walking and standing activity.

The second stage involves feature extraction. There are 11 such features which are computed along the second dimension of the data array. The 11 features are list below:

1. SAV – Sum of absolute values

$$\mathrm{SAV} = \sum_{k=1}^{n} |A_k| \qquad [1]$$

Where A – amplitude of the signal.

n – number of samples.

2. MSAV – Mean of SAV

$$\mathrm{MSAV} = 1/n \sum_{k=1}^{n} |A_k| \qquad [2]$$

3. Weighted Mean 1

$$\mathrm{WM1} = 1/n \sum_{k=1}^{n} |A_k| * w_k \qquad [3]$$

Where, w_k =1 ; for 0.25*n ≤ A ≤ 0.75*n

W_k – 0.5 ; otherwise

4. Weighted Mean II

$$\mathrm{WM2} = 1/n \sum_{k=1}^{n} |A_k| * w_k \qquad [4]$$

w_k =1 ; for 0.25*n ≤ A ≤ 0.75*n

w_k=4*k/n ; for 0.25*n> A

w_k = =4*(k-n)/n ; for 0.75*n< A

5. Energy

$$E = \sum_{k=1}^{n} |A_k|^2 \qquad [5]$$

6. Variance

$$\mathrm{VAR} = \frac{1}{n-1} \sum_{k=1}^{n} (A_k - \mu)^2 \qquad [6]$$

where μ is the mean of the selected window samples.

Window size = 25 samples

7. Root Mean Square

$$\mathrm{RMS} = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (A_k - \mu)^2} \qquad [7]$$

8. Gradient Sum

$$GS = \sum_{k=1}^{n-1} A_{k+1} - A_k)^2 \qquad [8]$$

9. Level Crossing

$$LC = \sum_{k=1}^{n-1}[f(A_k * A_{k+1}) \cap f(|A_k - A_{k+1})] \quad [9]$$

10. Slope Change

$$SC = \sum_{k=2}^{n-1}[f(|A_k - A_{k-1}| \times |A_k - A_{k+1})] \quad [10]$$

11. Willison Amplitude

$$WA = \sum_{k=2}^{n} f(|A_k - A_{k-1}|) \quad [11]$$

f(n) is the threshold function that returns one when n is greater or equal to the defined threshold value, otherwise it returns zero.

At this moment, the values of $(A_k * A_{k+1})$, $|A_k - A_{k+1}|$, and $(|A_k - A_{k-1}|) \times (|A_k - A_{k+1})$of all data were calculated. The threshold is selected as the median value;thus, it can distinguish intensive and non-intensive movement.

Considering 25 samples for each of the above feature calculation as an window, we have 4000/25 equals 160 samples over the second dimension of the array. And corresponding to 9 sensors the total matrix size will be 99x160 when all the sensor features are vertically concatenated for each human activity. Experiments were conducted with 99 features as an input to ANN, but the network was unable to train for the minimum permissible error. It was tried with different topologies and various transfer functions combination, but the network would either converge or unable to achieve higher accuracy. Therefore, it was decided to reduce the features since most of the feature rows of an activity when compared to other two activities did not show much variance. After efforts and experiments, the following row index were finalized for the selection of the feature row. The 27 row indices were:

idx=[6,7,8,17,18,19,28,29,30,39,40,41,50,51,52,61,62, 63,72,73,74,83,84,85,94,95,96];

Thus, out of 99 rows, only 27 rows were used for training and testing.Thus, the data vector remained after removal of non-cooperating rows was of dimension 27x160 for each activity. After selection process, number of samples for training and testing was chosen to be 75:25%. That is 120 samples of each activity was separated for training and 40 samples were isolated for testing.

The Artificial NN was used with the following parameters:

Sr. No.	Parameter	Value
1	Hidden Layers	3
2	Neuron Configuration for each layer	[6 8 1]
3	Transfer functions	[tansigtansigpurelin]
4	Epoch	1000
5	Minimum Gradient	10^{-12}
6	Step size	0.01
7	Goal Set	10^{-15}
8	Parameter	MSE

Table 1 – ANN specifications used for classification of human activities

RESULTS & CONCLUSIONS

The ANN was trained using the first 120 samples of each activities with 27 (Out of 99) features from all sensors and remaining 40 samples were tested. The classification accuracy for training and test samples was **100 and 99.1667%.** To validate our result, a 10-cross fold-validation was performed over all samples. 480 samples were divided into 10 groups and each test group of 48 samples was then tested against 432 training samples. The following result was obtained.

Sr. No.	Test Sample	Training Accuracy	Testing Accuracy
1	1:48	99.537	100
2	49:96	99.7685	97.9167
3	97:144	99.537	97.9167
4	145:192	100	100
5	193:240	99.537	100
6	241:288	99.7685	100
7	289:336	100	97.9167
8	337:384	100	100
9	385:432	100	100
10	433:480	100	99.1667
Average		99.8148	99.2917

Table 2 – ANN performance for 10-cross fold validation

From the above table 2, it is seen that two conclusions can be drawn. The network is one case is able to train the samples properly but fails to classify the test sample. On the other hand, in some cases the network fails to train accurately, but succeed in testing the sample to 100%. Rather in three cases the networks training and testing accuracy is 100%. Considering the average accuracy of training and testing an accuracy of **99%** is acceptable in classifying the human activities. The performance can be improved further by tuning the ANN parameters properly or selecting the features more precisely. Also, before training and testing, the data was normalized by dividing all the data set by the maximum value. This may have made some of the samples to lie close to each other and hence the network was unable to train or test the sample properly. A non-overlapping window of 25 samples was used for feature extraction. Making the window to overlap can also help in boosting the performance of the system. Features based on entropy, log, nearness can also be extracted and added so that more information can be given to the classifier. Comparing with the work done by S. Archasantisuk, T. Aoyagi, and T. Uusitupa [15], the minimum and maximum accuracy they achieved with 6 and 8 features was **90.48 and 98.91 and 90.41 and 99.08** respectively with Neural Networks.

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