ECG Signals Classification Based on Discrete Wavelet Transform, Time Domain and Frequency Domain Features

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Abstract— **The heart is the most vital organ in the human body. Without it, the body becomes lifeless since its function is to pump oxygenated and deoxygenated blood throughout the whole body. Heart disease has becoming the primary cause of death. ECG signal is commonly used to detect heart diseases. The ECG signal is initially in the time domain formed. In this paper, the fast Fourier transform and discrete wavelet transform were used to transform ECG signals in order to get significant features to be compared with features directly acquired from time domain ECG signal analysis. The time domain ECG input signals were taken from the Physionet website. Then, the signals were changed into frequency domain using FFT and DWT was applied to the ECG signal for Discrete Wavelet Transform analysis. The features found from these three domains were analyzed and compared.**

Keywords—time domain; FFT; DWT; ECG signal; heart disease

I. INTRODUCTION

The heart is the most important organ in the human body. It is built up of myogenic muscular organ that has a circulatory system responsible for pumping oxygenated and deoxygenated blood throughout the blood vessel by contracting repeatedly and in a structured rhythm. As stated by the World Health Organization (WHO), Cardiovascular Diseases (CVDs) are the number one cause of death worldwide. Many people died from CVDs than any other cause and it is estimated that 17 million people die of Cardiovascular Diseases (CVDs) especially by heart attacks and strokes, annually [1].

A. Heart Disease (Myocardial Infarction)

There are many types of heart diseases which had been diagnosed. Some of the diseases are categorised based on which part of the heart is damaged or not properly functioning: for example left-side heart failure and right-side heart failure. Coronary artery disease happens when arteries carrying blood to the heart muscle is blocked mainly by cholesterol and fats. Arrhythmia is a very common heart disease whereby it happens because on an irregular/abnormal heart beat [2]. In this paper, the type of heart disease that will be analysed is the Myocardial Infarction (MI). Myocardial Infarction is actually the medical term for heart attack. MI occurred when the blood did not flow properly to parts of the heart making an injury to the heart muscle due to lack of oxygen. This mainly happens because one of the coronary arteries which are supposed to supply blood to the heart builds up a blockage due to an unstable development of white blood cells, cholesterol and fat. A person having an acute MI usually has sudden chest pain that is felt behind the breast bone and sometimes travels to the left arm or the left side of the neck. Additionally, the person may have shortness of breath, sweating, nausea, vomiting, abnormal heartbeats, and anxiety [3]. The phrase "heart attack" is sometimes used incorrectly to describe sudden cardiac death, which may or may not be the result of Acute Myocardial Infarction (AMI). A heart attack can cause cardiac arrest, which is the stopping of the heartbeat, cardiac arrhythmia and abnormal heartbeat. However, severe MI may also lead to heart failure [4].

B. ECG Signal

The most reliable and common method to analyze heart disease is by using the ECG signal. ECG signal is a physiological signal. It is a non-linear and a non-stationary signal. The ECG signal is acquired easily without causing pain to the patient since it is collected non-invasively by placing ECG electrodes on specific locations throughout the surface of the human skin. The ECG signal is actually the acquired electrical activity of the heart across the thorax or chest. Each cell membrane that forms the outer covering of the heart has charges which depolarized with every heartbeat. An electrocardiogram (ECG) is a test that records the electrical activity of the heart, measures rate and regularity of heartbeats including the size and the chamber position. It can also detect the presence of any damage to the heart and also the hearts condition if affected by the use of drugs and devices such as the pacemaker. The term “lead” for an ECG is basically the voltage difference between two of the electrodes. This is the difference which is recorded by the equipment. The ECG signal has low amplitude voltages when obtained in the presence of high offsets and noise [5]. Commonly, only Lead II of the ECG signal is needed for further signal processing.

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The ECG signal consists of P, Q, R, S and T waves as shown in *Fig. 1*

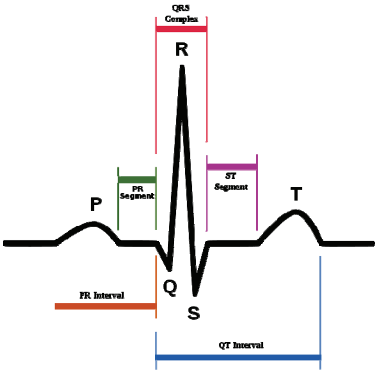


Fig. 1. ECG signal representing one complete heartbeat

C. *Time Domain*

Time domain is actually how the signal changes over a period of time. It is the analysis of mathematical functions, physical signals or time series of a set of data with respect to time. In time domain, the signal or function's value is known for all real numbers, for the case of continuous time, or at various separate instants in the case of discrete time [6]. Like in ECG signal for example, time domain refers to variation of amplitude of the ECG signal with respect to time [7]. From previous studies it is stated that in ECG monitoring, when several kinds of abnormalities happened, they will affect the morphology of the signal making the boundaries of the waves hard to localize [8]. This is why signal processing of ECG signal in time domain will give inefficient result compared to signal processing in frequency domain [8].

D. *Frequency Domain*

Frequency domain basically refers to how much the signals lie in a frequency range. It is the analysis of mathematical functions or signals with respect to frequency, rather than time [9]. This domain can also give information on the phase shift that must be applied to each sinusoid in order to be able to recombine the frequency components to recover the original time signal [10]. For example, in ECG signal with a number of peaks of different types will give variations in amplitude as well. Therefore, in frequency domain, the number of peaks that happens in an entire period of time is recorded. It is actually the number of times each event has occurred during total period of observation. It is much simpler than time domain as only the key points in a total interval are taken for analysis compared to time domain where every variation that occurs must be taken into account [7].

E. *Discrete Wavelet Transform*

DWT has become a common signal processing tool nowadays. The wavelet transform is implemented using a discrete set of wavelet scales and translations by obeying some defined rules [11]. Thus, in numerical analysis and functional analysis, DWT is the wavelet transform whereby the wavelets are discretely sampled [12].

II. METHODOLOGY

A. *Database*

Physionet is a free web access to large collections of recorded physiological signals. From here, the Physikalisch-Technische Bundesanstalt (PTB) database is taken as an input signal for this research since it contains the highest number of patients with an ECG sample of myocardial infarction. The specifications of the signal are as below:

- 16 input channels, (14 for ECGs, 1 for respiration, 1 for line voltage)
- Input voltage: ±16 mV, compensated offset voltage up to ± 300 mV
- Input resistance: 100 Ω (DC)
- Resolution: 16 bit with 0.5 µV/LSB (2000 A/D units per mV)
- Bandwidth: 0 - 1 kHz (synchronous sampling of all channels)
- Noise voltage: max. 10 µV (pp), respectively 3 µV (RMS) with input short circuit
- Online recording of skin resistance

The database contains 549 records from 290 subjects (aged 17 to 87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6; ages were not recorded for 1 female and 14 male subjects). Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals: the conventional 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs (vx, vy, vz). Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV. The diagnostic classes of the remaining 268 subjects are summarized in *"Table 1"*.

TABLE 1. Diagnostic class and number of subjects from database

Diaiagnostic class	Number of subjects
Myocardial infarction (MI)	148
Cardiomyopathy/Heart failure	18
Bundle branch block	15
Dysrhythmia	14
Myocardial hypertrophy	7
Valvular heart disease	6
Myocarditis	4
Miscellaneous	4
Healthy controls	52

B. *Pre-processing of ECG Signal*

The pre-processing of ECG signal consists of the filtering method. There are 4 main types of filters which are widely used in signal processing namely low pass, high pass, band pass and band stop filters. These filters are used in order to get an input signal that is pure and not contaminated with unwanted signal like noise and power line interference. These unwanted signals are called artefacts and are harder to be filtered especially for the ECG signal since there is a substantial spectral overlap between the ECG and muscle noise. The filters which are designed in an ECG signal processing system are mainly to remove artefacts of baseline wanders and power line interference. These artefacts need the design of a narrowband filter [13]. It is important that in order to perform filtering techniques on an ECG signal, the desired information within the ECG signal remains undistorted. In this research, a Butterworth low pass filter is used for both power line interference and baseline drift removal.

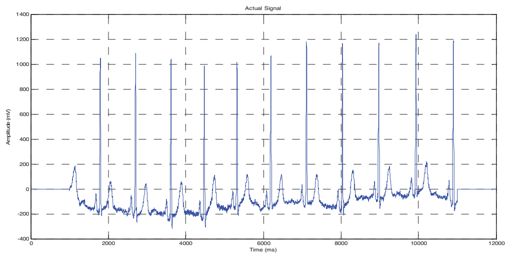
C. *Feature Extraction*

The purpose of feature extraction is to generate a feature vector from raw ECG signal. The feature vectors include QRS complex, S-wave and J point detection for ST shape classification, QRS width, QT intervals, R height, T height, and much more [14]. Those features stated are the morphological features and analysed in time domain forms. Some other approaches like wavelet transforms [15, 16] which is transform into frequency domain are also studied. These 2 domains are the beginning step for feature extraction techniques. In frequency domain analysis (spectral analysis) by using Fast Fourier transformation, the statistical features can be extracted. Many researches have been done on the feature extraction techniques of the ECG signal and it can be seen that frequency domain analysis is preferable rather than time domain analysis [8]. In the study, another technique is applied on the ECG signal which is the discrete wavelet transform.

i. *Time Domain*

The raw ECG signal from the database is uploaded in the time domain form as in *Fig. 2*. From here, the statistical features of mean, variance and standard deviation are taken directly from the ECG signal.

(a) Normal sample p104/s0306



(b) MI sample p010/s0036

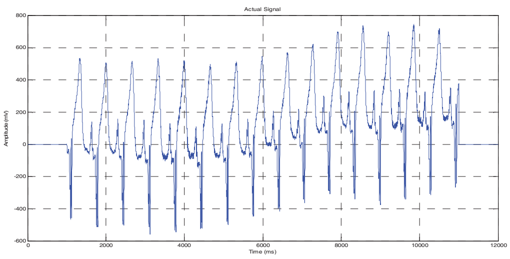


Fig. 2. ECG signal in time domain form for different types of sample

TABLE 2. Subjects and statistical features in time domain

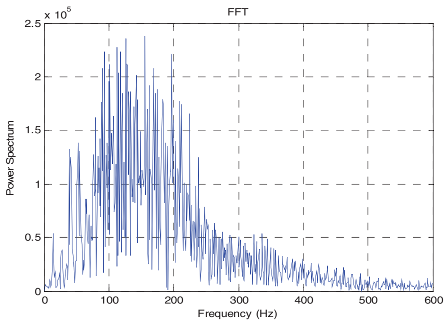
No.	Patient ID	Statistical Feature		
		Mean	Variance	Standard Deviation
1	patient104/s0306lre	-55.495	25678.97	160.25
2	patient105/s0303lre	317.039	50478.54	224.67
3	patient116/s0302lre	237.474	61277.28	247.54
4	patient117/s0291lre	118.430	43803.54	209.29
5	patient117/s0292lre	-101.048	43067.14	207.53
6	patient001/s0010_re	230.666	73898.14	271.84
7	patient001/s0014lre	90.187	111174.75	333.43
8	patient001/s0016lre	-90.495	92012.00	303.33
9	patient002/s0015lre	314.554	43567.11	208.73
10	patient003/s0017lre	603.085	150225.44	387.58927
11	patient249/s0484_re	190.463	110014.57	331.68
12	patient269/s0508_re	-383.174	98110.37	313.23
13	patient271/s0509_re	382.065	107577.17	327.99
14	patient272/s0510_re	207.051	59024.12	242.95
15	patient171/s0364lre	-609.473	206524.2	454.45

Patient number 1 until 5 is the normal sample. Patient number 6 until 10 is the myocardial infarction (MI) sample. Patient number 11 until 15 is categorized as others.

ii. *Frequency Domain*

Lead II of the ECG signal was changed from time domain into frequency domain. In this research, the Fourier transform is used by turning time domain signals onto a frequency domain signals. The frequency domain is represented by the spectrum of frequency components in a signal [10] as shown in *Fig. 3*. From that, the statistical features as in time domain are extracted consist of maximum point, minimum point, mean, variance and standard deviation.

(a) Normal sample p104/s0306



(b) MI sample p010/s0036

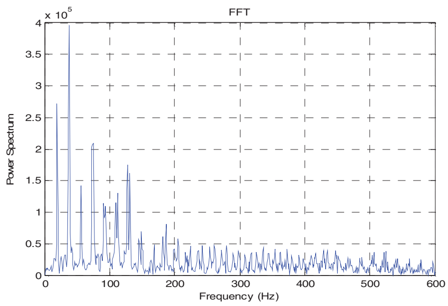


Fig. 3. ECG signal in frequency domain form for different types of sample

TABLE 3. Subjects and statistical features in frequency domain

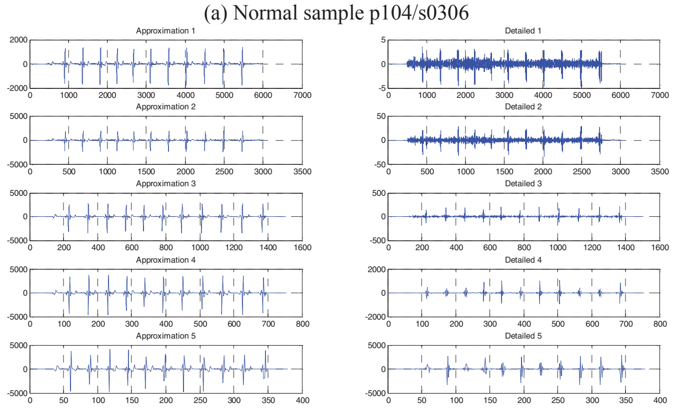
No.	Statistical Feature				
	Maximum Point	Minimum Point	Mean	Variance	Standard Deviation
1	237893.21	0.001	43970.07	2730796998	52257.03
2	309410.23	0.006	42606.93	2553355135	50530.73
3	207875.38	0.004	37973.29	1704426307	41284.70
4	521411.34	0.002	49961.02	5584208096	74727.56
5	812495.64	0.001	81786.58	18921692091	137556.14
6	884951.85	0.004	51293.95	9095646256	95371.10
7	1034826.38	0.002	56192.26	13990406686	118281.05
8	875822.88	0.002	63345.36	12941975652	113762.80
9	243539.74	0.006	37679.00	2208526080	46994.96
10	418945.80	0.011	38548.71	3734591607	61111.31
11	-10844435911	538378	84942.98	10844540049	104137.12
12	-3686375887	360923.36	49464.69	3686436603	60716.03
13	-6223886138	396003.72	57055.45	6223965030	78892.11
14	-5831257003	376713.01	58022.16	5831333366	76363.17
15	-11463039835	650093.95	77754.30	11463146901	107066.09

Patient number 1 until 5 is the normal sample. Patient number 6 until 10 is the myocardial infarction (MI) sample. Patient number 11 until 15 is categorized as others.

iii. Discrete Wavelet Transform

In DWT, the decomposition level was set at level 5 by using the daubechies wavelet of order 3 (db3) as shown in *Fig. 4*. The feature extracted here is only statistical value of standard deviation. The statndard deviation extracted are values from all 5 level of the detailed coefficient and 1 value from only the last level which is level 5 of the approximation coefficeint. This makes the total statistical input from one sample of ECG signal using DWT techniques will be equal to 6.

(a) Normal sample p104/s0306



(b) MI sample p010/s0036

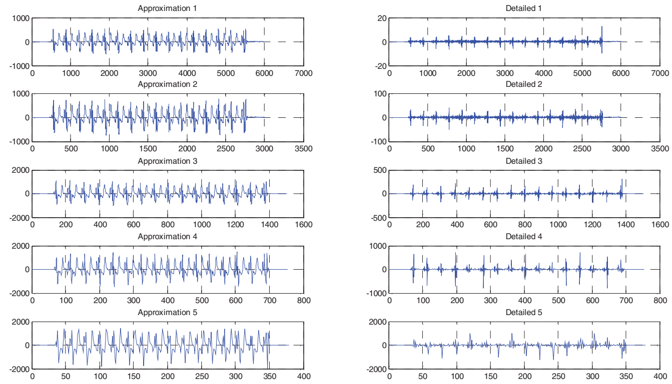


Fig. 4. DWT applied to the ECG signal up to level 5 for different types of sample

TABLE 4. Subjects and standard deviation values for 5 level of DWT

No.	Standard Deviation					
	D1	D2	D3	D4	D5	A5
1	0.59	4.47	23.27	129.25	612.98	907.37
2	0.84	5.95	26.29	139.42	560.86	895.03
3	1.02	7.48	32.52	142.21	503.45	733.36
4	0.72	5.55	25.38	152.21	674.24	1278.08
5	0.67	5.02	23.65	149.63	819.29	1217.14
6	1.89	12.77	42.24	149.97	710.33	1597.53
7	3.50	24.42	77.05	198.91	681.85	1997.44
8	4.56	31.18	94.46	191.97	975.86	1860.30
9	1.51	10.70	36.76	117.58	478.90	838.30
10	1.01	6.75	29.99	114.09	528.29	1036.47
11	0.86	6.84	44.84	273.65	1066.22	1866.20
12	0.84	5.58	30.60	127.00	548.84	1135.04
13	0.85	4.86	28.59	130.57	697.07	1408.53
14	1.34	9.59	39.27	154.48	679.82	1385.86
15	1.20	8.80	39.1	178.55	961.45	1907.6

Patient number 1 until 5 is the normal sample. Patient number 6 until 10 is the myocardial infarction (MI) sample. Patient number 11 until 15 is categorized as others

III. CLASSIFICATION

There are so many techniques for classifying an ECG signal especially for detecting heart diseases. Each method used depends on the ECG segments/interval and also features which is to be analyze. The most common and effective classifier used is the artificial neural network (ANN). ANN functions by processing information like the humans' biological nervous system. ANN can put together information of a specific application like pattern recognition and data classification by a process of learning [17]. ANN is organized in layers which are made up of a number of interconnected 'nodes' which contains an activation function. The patterns which we have are given to the network through the input layer which communicates to one or more hidden layer and where the actual processing is done through a system of weighted connections. The hidden layer will link to the output layer [18].

A. Multilayer Perceptron

Artificial Neural Network (ANN) is one of the most used data mining method to extract patterns in an intelligent and reliable way [19, 20]. Multilayer perceptron (MLP) is an example of an ANN classifier. In the current study, a MLP classifier trained using Lavernberg Marquadt learning algorithm is used. The neurons are connected by links. Each link has a numerical weight associated with it. The weights will express the strength or importance of each neuron input. With this, the MLP learns through repeated weight adjustment [17]. For this part, a MLP neural network with Lavernberg Marquadt training algorithm is used for classification between 3 categories which are normal, Myocardial Infarction (MI) and others. The number of output node is 3 and the activation functions used are *tansig* function for hidden nodes and *logsig* function for output nodes. The analysis of hidden node and epoch are tested one by one. The hidden node is set to be 5, 10, 15, 20 and 25, whereas, the epochs are set at 50, 100, 500 and 1000. From here, the best hidden node and epoch giving the highest accuracy, sensitivity and specificity can be determined.

IV. RESULT

For accurate classification, the sample waveforms are divided into training and testing in the ratio of 70% and 30% respectively. Training is done repeatedly by changing the number of hidden node and epoch in order to get the highest accuracy. The results of sensitivity, specificity and accuracy for time domain, frequency domain and DWT is shown in "Table 5," "Table 6," and "Table 7,".

TABLE 5. Testing result for time domain analysis

Hidden	Epoch	Sensitivity (%)	Specificity(%)	Accuracy(%)
5	50	90.91	8.33	78.21
	100	90.15	16.67	78.85
	500	89.40	79.17	81.41
	1000	90.15	37.5	82.05
10	50	87.12	66.67	83.97
	100	91.67	91.67	91.67
	500	95.45	91.67	94.87
	1000	95.45	91.67	94.87
15	50	94.67	83.33	92.95
	100	95.45	83.33	93.59
	500	95.45	87.5	94.23
	1000	95.45	87.5	94.23
20	50	89.34	41.67	82.05
	100	94.67	91.67	94.23
	500	94.67	91.67	94.23
	1000	94.67	91.67	94.23

TABLE 6. Testing result for frequency domain analysis

Hidden	Epoch	Sensitivity (%)	Specificity(%)	Accuracy(%)
5	50	86.36	37.5	78.85
	100	86.36	29.17	77.56
	500	87.88	29.17	78.85
	1000	90.15	29.17	80.77
10	50	93.18	75	90.38
	100	93.94	75	91.03
	500	95.45	75	92.31
	1000	95.45	75	92.31
15	50	93.94	58.33	88.46
	100	96.21	83.33	94.23
	500	96.21	100	96.79
	1000	96.21	100	96.79
20	50	91.67	50	85.26
	100	96.97	83.33	94.87
	500	96.97	83.33	94.87
	1000	96.97	83.33	94.87

TABLE 7. Testing result for DWT analysis

Hidden	Epoch	Sensitivity (%)	Specificity(%)	Accuracy(%)
5	50	90.91	83.33	89.74
	100	91.67	83.33	90.38
	500	93.18	83.33	91.67
	1000	93.18	83.33	91.67
10	50	91.67	83.33	90.38
	100	92.42	83.33	91.03
	500	93.18	83.33	91.67
	1000	93.18	83.33	91.67
15	50	87.88	41.67	80.77
	100	98.49	87.5	96.79
	500	99.24	87.5	98.72
	1000	99.24	87.5	98.72
20	50	90.91	83.33	89.74
	100	96.21	87.5	94.87
	500	96.21	87.5	94.87
	1000	96.21	87.5	94.87
25	50	93.18	75	90.38
	100	96.97	87.5	95.51
	500	97.73	87.5	96.15
	1000	97.72	87.5	96.15

V. CONCLUSION

From the results, it is seen that by doing further processing of the ECG signal an accurate and dependable result can be achieved to classify the ECG signal. As we can see, the highest accuracy is obtained from DWT signal processing which gives accuracy up to 98.72% followed by 96.79% in frequency domain analysis and finally the time domain gives an accuracy of 94.87%. Although DWT only has 1 feature which is standard deviation compared to time and frequency domain which has 5 features (maximum point, minimum point, mean, variance and standard deviation), still DWT gives the highest results.

ACKNOWLEDGMENT

I would like to express my appreciation to those charitable people at PhysioNet website, which offer free web access to large collections of recorded physiological signals where the database had been taken.

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