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Extraction and Study of Heart Rate Variability (HRV) Parameters in Various Diseased Conditions

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Abstract **Heart Rate Variability (HRV) is one of the important physiological signals diagnosis tool, but still it is not considered for diagnosing diseases using HRV parameters. In this work HRV parameters including linear and nonlinear parameters were analyzed using two different available tool, Kubios HRV written in MATLAB platform and Biomedical Workbench tool written in LABVIEW platform. Each tool has its own advantages and own list of HRV variables, but most of the variables used for the study are similar in both the soft wares. The data required for analysis of HRV is taken from the physionet database, where there is wide range of data available with different diseased conditioned states. The HRV parameters were extracted using the available tool kits and HRV parameters under different diseased conditions like Congestive Heart Failure (CHF), Arrhythmia, stroke patients, hypertensive subjects, subjects under medications, apnea individuals. The data with the normal subjects were compared with that of the diseased subjects.**

Keywords —HRV, Kubios HRV, Biomedical Workbench, Congestive Heart Failure, Apnea

I. INTRODUCTION

The main causes for cardiovascular disease (CVD) are a disorder that arises in the heart and blood vessels [1]. There are many reasons for the disorders caused some of them are raised blood pressure (hypertension), cerebrovascular disease (stroke), coronary heart disease (heart attacks), heart failure and congenital heart diseases. World health organization (WHO) estimated that 170.3 lakh people died from CVD according to its report in 2008. The deaths because of CVD are more in low and middle income countries. According to WHO report it is estimated that 230 lakh people dies because of CVD every year by 2030. Heart failure is becoming one of the major reasons for death during CVD. Congestive heart failure (CHF) becomes very critical for lungs and tissues in the body when heart fails to pump blood sufficiently to these parts [2, 3]. CHF may result in fatigue, shortness of breath and diminished exercise capacity. Hence it is very important to diagnosis the CVD at the earliest, so that the person affected can take precautions and can also take immediate measures. Electrocardiogram (ECG) is commonly utilized for diagnosis the diseases related to heart [4]. ECG has grown its vitality because of its non invasive nature of measurements. From ECG we can derive heart rate variability (HRV) and its parameters can be used as the diagnosis tool of CVD. HRV can be defined as the time interval between two successive R-waves (QRS complex of ECG) or the variation of time between successive heartbeats [8,9]. The human heart does not beat with a fixed rhythm, the heart rhythm keeps varying, and its time is about 0.5 to 2 seconds. The rhythm of the heart beat is changed by the Autonomic Nervous Systems (ANS), its keep changing because of the activity of sympathetic and parasympathetic functions of the ANS. ANS cannot controls the body functions in controlled way for instance like functions like excitement, digestions, breathing [11]. HRV is an important tool of accessing the ANS functions noninvasively and hence it is an indicator of stress, sleep, apnae, metabolic, respiration rate, stiffness etc. HRV also changes with gender, individual age, habits, demography of the individual. HRV proves to predict diabetes,arrhythmia, ventricular fibrillation. The normal heart beat ranges between 60 to 10 bets per minute, similarly there are no standard values available for HRV parameters.There are various tools available of analyzing HRV[10]. The essential signals for analysis can be obtained from the database that includes BIDMC Congestive Heart Failure Database (chfdb), MIT-BIH Normal Sinus Rhythm Database (nsrdb), Normal Sinus Rhythm RR Interval Database (nsr2db). Physionet is the bank of signals available for researchers for free of cost. There are wide ranges of signals from measuring short duration signals (1 minute) to long duration signals (upto 24 hours) Most of the signals are available for free, it is also available in different format and one can use the format which they intends.

II.MATERIAL AND METHODS

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HRV can be In this work signals are obtained from the physionet data base and it has been analysed for HRV measurements using Kubios HRV tool and Biomedical workbench tool. The signals were taken for different conditioned and compared it with normal subjet data. Kubios HRV is a tool written in MATLAB platform and Biomedical Workbench tool is created in LABVIEW platform by National Instruments.

Physionet database is the database where biomedical signals are stored. The Pysiobank ATM contains the ECG signals of different diseased conditions. The Phsiobank ATM GUI is as shown in the fig.1. The ECG signals desired can be obtained by selecting the dropdown from the database.

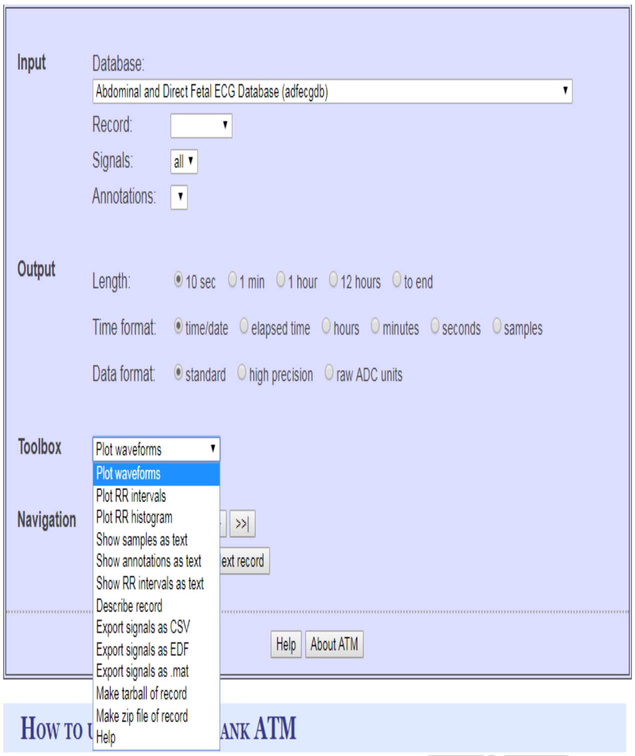

Fig.1 GUI of PhysioBank ATM

Signals can be obtained from the PhysioBank ATM of different length, time format, data format. From the toolbox we can also save the recording in the desired output format. The stored data is used for offline analysis of HRV using Kubios HRV and Biomedical Workbench tool.

KUBIOS HRV TOOL

Kubios tool analyses the HRV in three main categories as frequency-domain, time-domain and nonlinear HRV variables. It supports wide range of data types like .ECG, .EDF, .txt, .SDF, .csv file and other types of data format. It enables to input signals to Kubios with various ECG signal acquisition systems. The time domain GUI is as shown in fig.2.

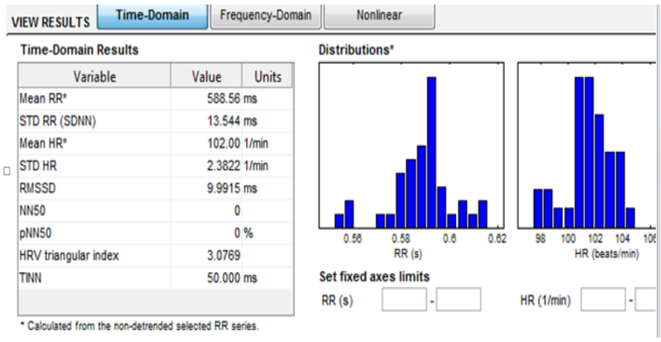

Fig.2 Time domain GUI

The power spectrum is obtained for the RR interval, based on the power spectrum frequencydomain signals are analysed using FFT spectrum method and AR spectrum method, the GUI is as shown in fig.3.

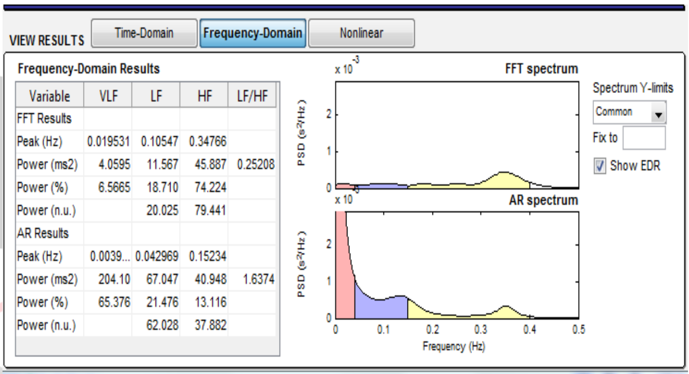

Fig.3 Frequency domain GUI

Poincare plot analysis , Entropy calculations, Detrended Fluctuation Analysis types of signal processing are carried in nonlinear GUI. The nonlinear GUI is as shown in fig.4.

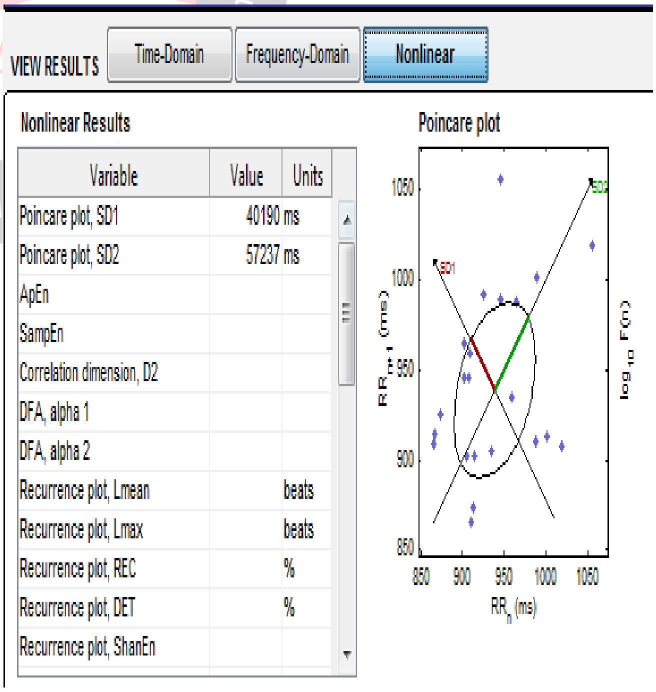

Fig.4 Nonlinear GUI

BIOMEDICAL WORKBENCH

This is the GUI created from LABVIEW specially designed for biomedical signal applications. The GUI is user friendly

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and application wise also simple and reliable. The biomedical workbench can also be used as the reliability test of the biomedical signal acquisition[8]. The GUI of the Biomedical Workbench and Heart Rate Variability Analyzer is as shown in the fig5 and fig6 respectively.

Fig.5 Biomedical Workbench tool

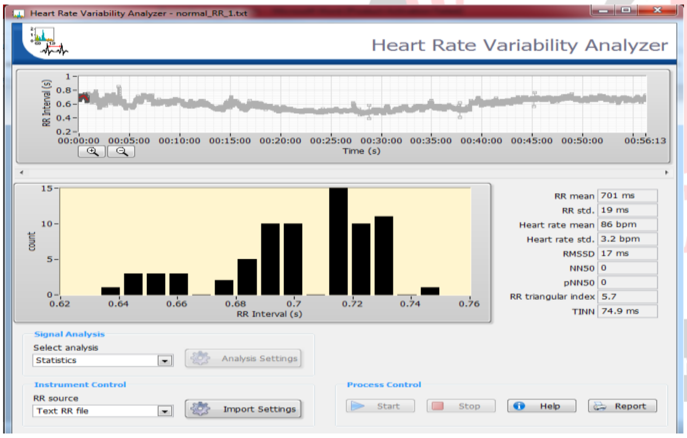

Fig.6 Heart Rate Variability Analyzer GUI

The tool takes RR intervals as input for HRV analysis. It analyses the statistical data, power spectral data and non linear parameters analysis like Poincare plot, Detrended Fluctuation Analysis and Entropy. The results can be exported to .html for further analysis and statistical study. The power spectral density of the normal subject and that of subject with Congestive Heart Failure is as shown in fig.7 and fig.8 respectively.

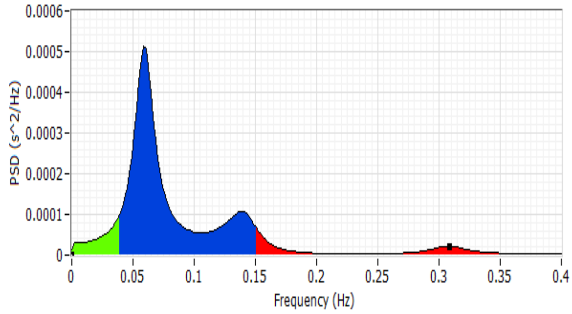

Fig.7 Power Spectral density of the normal subject

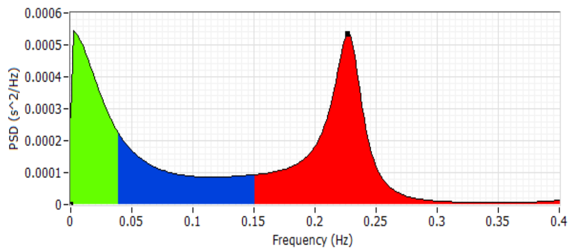

Fig.8 Power Spectral density of the patient with Congestive Heart Failure.

The changes in the statistical parameters, spectral densities and nonlinear parameters of RR intervals one can be to determine the normal functionality of the heart.

III.RESULTS AND DISCUSSIONS

The BIDMC Congestive Heart Failure Database consists of ECG recordings of 15 subjects who are suffering from congestive heart failure and Congestive Heart Failure RR interval database which contains long term ECG recording off 29 subjects. Sampling rate used in 128 samples for a second. Normal signals are obtained by normal sinus rhythm database of physionet.

Table.1 Comparision of HRV analysis of Controlled subjects and subjects with Conjective Heart Failure

Parameter	Controlled Subjects	Conjective Heart Failure Subjects
HR (mean ± SD)	65±26	90±13
SDNN (ms) (mean ± SD)	151±25	114±10
RMSSD (mean ± SD)	78±23	34±19
pNN50(%)	5.52±6.35	3.93±2.65
LF (ms^2) (mean ± SD)	87±29	43±26
HF (ms^2) (mean ± SD)	66±12	18±11
LF/HF (mean ± SD)	5±3.7	2±1.97
TINN(ms)	83.82±39.34	91.51±61.87
DFA(α1)	1.39±0.19	0.99±0.26
DFA(α2)	1.06±0.13	1.21±0.17
CD	3.43±0.05	2.35±0.28
Ap En(%)	86±32	53±13

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SampEn(%)	77±28	52±18

MIT-BIH Arrhythmia database contains ECG recordings of 137 subjeccts with Arrythmia.

Table.2 Comparision of HRV analysis of Controlled subjects and subjects with Arrhytmia

Parameter	Controlled Subjects	Arrhytmia Subjects
HR (mean ± SD)	65±26	67±5
SDNN (ms) (mean ± SD)	151±25	112±35
RMSSD (mean ± SD)	78±23	54.6±41.5
pNN50(%)	5.52±6.35	4.83±3.85
LF (ms^2) (mean ± SD)	87±29	51±25
HF (ms^2) (mean ± SD)	66±12	20±12
LF/HF (mean ± SD)	5±3.7	5.1±3.6
TINN(ms)	83.82±39.34	86.51±51.98
DFA(α1)	1.39±0.19	1.12±0.56
DFA(α2)	1.06±0.13	1.29±0.29
CD	3.43±0.05	2.33±0.12
Ap En(%)	86±32	43±26
SampEn(%)	77±28	49±36

The long-term Arterial Fibrillation (AF) database having 84 long-term recordings of the ECG signals with subjects with arterial fibrillation most of it is paroxysmal kind. The MIT-BIH atrial fibrillation is the database where 25 long term recordings of the ECG signals are made available.

Table.3 Comparision of HRV analysis of Controlled subjects and subjects with Arterial Fibrillation Subjects

Parameter	Controlled Subjects	Arterial Fibrillation Subjects
HR (mean ± SD)	65±26	86±35
SDNN (ms) (mean ± SD)	151±25	94±13
RMSSD (mean ± SD)	78±23	63±17
pNN50(%)	5.52±6.35	3.28±1.98
LF (ms^2) (mean ± SD)	87±29	56±24
HF (ms^2) (mean ± SD)	66±12	17±14
LF/HF (mean ± SD)	5±3.7	4±2.83
TINN(ms)	83.82±39.34	90.21±63.75
DFA(α1)	1.39±0.19	1.11±0.38
DFA(α2)	1.06±0.13	1.42±0.26
CD	3.43±0.05	4.01±0.16
Ap En(%)	86±32	62±32
SampEn(%)	77±28	55±23

Effect of drugs on HRV parameters is studied with CiPA database. It is the database containing ECG recordings of 60 subjects who are medication like ranolazine, chloroquine, verapamil, dofetilide.

Table.4 Comparision of HRV analysis of Controlled subjects and subjects under medication.

Parameter	Controlled Subjects	Under Medication Subjects
HR (mean ± SD)	65±26	85±13
SDNN (ms) (mean ± SD)	151±25	124±11
RMSSD (mean ± SD)	78±23	54±21
pNN50(%)	5.52±6.35	3.45±3.05
LF (ms^2) (mean ± SD)	87±29	63±32
HF (ms^2) (mean ± SD)	66±12	21±12
LF/HF (mean ± SD)	5±3.7	4±3.9
TINN(ms)	83.82±39.34	96.51±58.56
DFA(α1)	1.39±0.19	0.82±0.42
DFA(α2)	1.06±0.13	1.17±0.19
CD	3.43±0.05	1.55±0.21
Ap En(%)	86±32	65±21
SampEn(%)	77±28	55±17

The data with stroke patient's ECG signals were studied using the database of physionet. In this database, ECG signals from 60 subjects suffering from strokes are available. All the signals had long term measurement data.

Table.5 Comparision of HRV analysis of Controlled subjects and subjects suffering from stroke

Parameter	Controlled Subjects	Individuals suffering from stroke
HR (mean ± SD)	65±26	93±23
SDNN (ms) (mean ± SD)	151±25	90±20
RMSSD (mean ± SD)	78±23	53±21
pNN50(%)	5.52±6.35	2.65±3.5
LF (ms^2) (mean ± SD)	87±29	52±38
HF (ms^2) (mean ± SD)	66±12	23±18
LF/HF (mean ± SD)	5±3.7	2±2.86
TINN(ms)	83.82±39.34	78.71±43.62
DFA(α1)	1.39±0.19	0.65±0.85
DFA(α2)	1.06±0.13	1.35±0.68
CD	3.43±0.05	2.12±0.24
Ap En(%)	86±32	61±23

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SampEn(%)	77±28	49±25

To derive the HRV parameters for hypertensive subjects SHAREE database is used. It contains ECG signals of 139 subjects with hypertensive and after 12 months of follow up 3 suffered from stroke, 11 suffered from myocardial infarctions and 3 suffered from syncopal events.

Table.6 Comparision of HRV analysis of Controlled subjects and Hypertensive Subjects

Parameter	Controlled Subjects	Hypertensive Subjects
HR (mean ± SD)	65±26	95±23
SDNN (ms) (mean ± SD)	151±25	144±21
RMSSD (mean ± SD)	78±23	64±31
pNN50(%)	5.52±6.35	2.45±3.85
LF (ms2) (mean ± SD)	87±29	42±28
HF (ms2) (mean ± SD)	66±12	31±25
LF/HF (mean ± SD)	5±3.7	4±2.32
TINN(ms)	83.82±39.34	99.85±63.73
DFA(α1)	1.39±0.19	0.91±0.57
DFA(α2)	1.06±0.13	1.34±0.88
CD	3.43±0.05	3.02±0.35
Ap En(%)	86±32	45±16
SampEn(%)	77±28	53±21

HRV parameters of subjects with Apnea were studied using Apnea ECG data base. The data base contains ECG data of 70 samples, recorded for a duration of around 7-10 hours.

Table.7 Comparision of HRV analysis of Controlled subjects and Apnea Subjects

Parameter	Controlled Subjects	Apnea Subjects
HR (mean ± SD)	65±26	73±13
SDNN (ms) (mean ± SD)	151±25	121±18
RMSSD (mean ± SD)	78±23	62±32
pNN50(%)	5.52±6.35	3.65±2.5
LF (ms^2) (mean ± SD)	87±29	63±38
HF (ms^2) (mean ± SD)	66±12	23±21
LF/HF (mean ± SD)	5±3.7	2.5±1.96
TINN(ms)	83.82±39.34	76.81±42.65
DFA(α1)	1.39±0.19	0.85±0.25
DFA(α2)	1.06±0.13	1.46±0.58
CD	3.43±0.05	2.21±0.53
Ap En(%)	86±32	65±31
SampEn(%)	77±28	53±28

1V. CONCLUSION

The major threat for this generation is the growing irregularities in the heart which might have caused due to various reasons. It is important to know the working of our heart at the regular intervals. In this regards one of the important tool available to access the functionality of the heart through Autonomic Nervous System(ANS) is HRV. In this detailed studies were carried on the HRV parameters in different diseased conditions which includes the time domain, frequency domain and nonlinear analysis of HRV. For extracting maximum of the variable two available toolkit for HRV, Kubios HRV and Biomedical Workbench tool were used. Both are user friendly GUIs and one can easily access the HRV parameters through these tools. The results showed the overall reduction in the variability of the heart beat. In diseased conditions the heart beats with the specific rhythm where as in normal conditions heart beats with random rhythm. These randomness of the heart beats are obtained by Entropy and Detrended Fluctuation Analysis methods. In hypertensive subjects the LF power is considerably reduced compared to normal individuals. In Congestive Heart failure subjects the RMSSD values were reduced by 32 percent. In arterial fibrillation and apnea patients the LF/HF values were considerably lower compared to normal individuals. Thus by analyzing the HRV values one can predict the future complications that may cause or one can be aware of the deprecation in there HRV values by regular monitoring. As HRV is one of the noninvasive and simple tool for diagnosing and predicting the diseases.

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