Intelligent Heart Rate Variability Processing System

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INTELLIGENT HEART RATE VARIABILITY PROCESSING SYSTEM

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Abstract— **In this research an expert system for automated detection of abnormality of heart rate variability. For this purpose, a data acquisition system from Holter ECG records, is developed by using QRS detection techniques for the future development of an standard ECG database. New and innovative medical applications based on developments in the wireless networks field are being developed in the research as well as commercial sectors. This trend has just started and we predict wireless networks are going to become an integral part of medical solutions due to its benefits in cutting down healthcare costs and increasing accessibility for patients as well as healthcare professionals. In this research we give some background on applications of wireless networks in the heart rate variability processing and discuss the issues and challenges. We have also tried to identify some of the standards in use. Another contribution due to this paper is the identification of innovative medical applications of wireless networks developed or currently being developed in the research and business sectors in Vietnam.**

Keywords— **Holter ECG records, HRV, Heart rate variability, wireless networks.**

I. INTRODUCTION

Electrocardiograms (ECGs) are used by medical professionals to monitor the heart of a patient. These devices usually operate with 12 leads connected to the patient's skin in a prescribed pattern. An ECG can be used to detect abnormal cardiovascular symptoms, measure heart rates, and monitor heart diseases. The most common non-medical application of an ECG is to measure a heart rate during a workout, however, the aim of this project is to prototype a device that could aid remote monitoring and feedback[1],[2].

A suitable procedure for cardiac surveillance should allow quasi-continuous and in most cases permanent, i.e. lifelong, and application. The used equipment should not constrain the patient in his daily routine activities and preferably not require special handling by the patient, but be forgettable if no risky situation is developing. There is increasing preliminary evidence that intramyocardial electrograms have the potential for efficient cardiac risk surveillance, especially if the system includes telemonitoring features, e.g. based on the Bluetooth and WLAN technology, cellular phone networks, intra- or internet technology or other global communication technologies which are already available, as well as advanced signal and information processing combined with powerful database systems.

The most stringent constraint until now is the limited processing capacity of the microprocessors which are used in implants, usually 16-bit devices and in many cardiac pacemakers still 8-bit devices. If more tasks have to be accomplished, e.g. pacing, then the total load for the battery may be another limiting constraint.

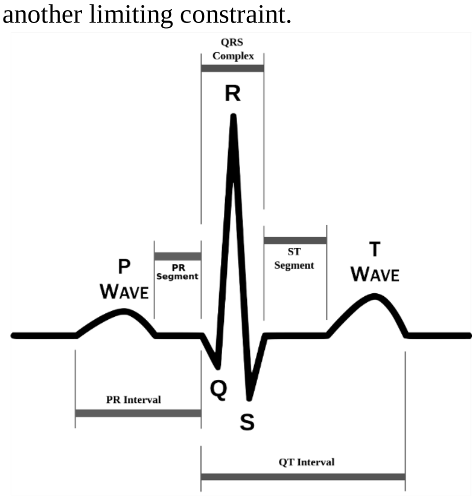

Fig. 1. ECG Parameters with P,Q,R,S,T wave

The most important components of the ECG that the device needs to report include P wave, QRS interval, and the T wave. These waveforms have the inherent issue that the measurable signals have amplitudes in the range of 0.1mV to 10mV. Another issue with these signals is that the smallest time components last as little as 50ms (The PR segment), or 80ms (The entire QRS complex). This short time means that the sample speed for the signal needs to be significantly less than 25ms to ensure adequate sampling. The polarization, depolarization, and contractions of the heart during the cardiac cycle produce signals which can be viewed on a device such as an oscilloscope [3]. The ECG signal can be visually represented by three major waves which are synchronized with the heart activity. The focus of the project relates to the basic measure that is related to the heart rhythm, the heart rate [4]. The heart rate simply describes the frequency of the cardiac cycle and is measured in contractions or beats per minute (bpm). Figure 1 illustrates the wave components of the ECG signal. The PR interval is the duration of time between the beginning of the P wave, signifying atria depolarization, and the beginning of the QRS complex. It represents the time between the beginning of the contraction of the atrium and the beginning of the contraction of the ventricle. The QT interval extends from the beginning of the Q wave to the end of the T wave. It represents the time of ventricular contraction and repolarization [5]. The ST interval extends from the S wave to the end of the T wave. The standard ECG parameter values are listed in the Table 1 below:

Table 1 QRS parameter

No.	Table Column Head		
	Parameter	*Ranger*	*Unit*
1	Heart Rate	60 – 150	Beats Per Minute
2	PR Interval	0.1 - 0.25	Seconds
3	QT Interval	0.29 ± 0.14	Seconds
4	P Wave Duration	0.12 ± 0.04	Seconds
5	QRS Width	0.05 – 0.1	Seconds
6	T Wave Duration	0.08 ± 0.02	Seconds

As mentioned previously, the electric field generated by the heart is best characterized by vector quantities, however, it is generally convenient to directly measure only scalar quantities, i.e. a voltage difference (in the mV order) between given points of the body. The primary signal characteristics of an ECG signal has a useful frequency range of about 0.05Hz to 150Hz. For this reason, a good low frequency response is essential to ensure baseline stability and a good high frequency response is needed for attenuation of high frequency noise from other signals of biological origin [6],[7].

II. METHODS

A. System block diagram

Model ECG signal acquisition are often used as a minimum of three probes in Figure 2 below. In this model, the ECG signal acquisition, low-pass, high-pass filter, 50Hz noise filtering and variable analog-to-digital ADC. The signal from the ADC can be handled in many different ways through the MSP430 microcontroller. This microcontroller can be connected to computer systems to exchange data the two-way ECG.

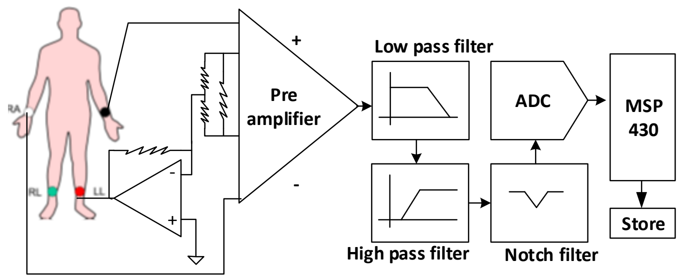

Fig. 2. Block diagram to receive ECG signals from patient

B. Intelligent Heart Rate Variability Processing System

Model ECG acquisition allows connection to many different inputs. Fig. 3. Intelligent Heart Rate Variability Processing System can be connected to the MSP430 module in Figure 2 or from the wireless block ECG, Holter, or from different sets. ECG data acquired will be synthesized and processed by a computer powerful enough configured through the software vendor or device through Matlab code, c #.

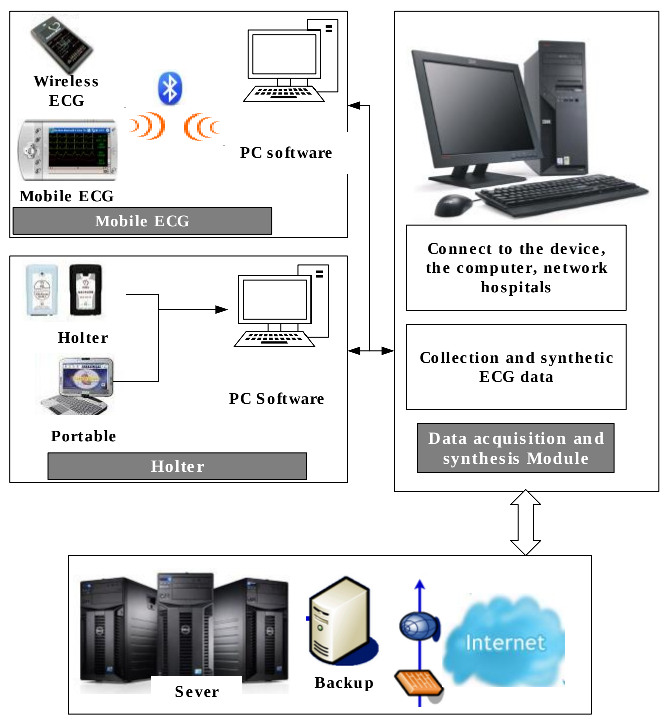

Fig. 3. Intelligent Heart Rate Variability Processing System

This Data acquisition and synthesis Module collect data and then transferr to an intermediate computer system. This machine connect to the device, the computer, network hospital, Collection and synthetic ECG data, stored in the database of the hospital network.

C. Multi Fluctualtion Detrended Analysis

Intervals between cardiac beats vary in a complex manner, presenting exponential correlations. Detrended fluctuation analysis is a method that allows the detection of long-range correlations embedded in an irregular signal, and avoids spurious detection of apparent long-range correlations that are an artifact to the object of the analysis [8]. In the context of HRV, DFA allows the distinction between complex fluctuations intrinsic to the nervous system in the command of vital actions of the human body, and those originated on the environment and that also influence the heart rate. Those fluctuations that are intrinsic to the nervous system happen to be observed throughout the signal, as opposed to the extrinsic fluctuations that present local and short term effects [9]. The main objective of DFA is to extract the extrinsic fluctuations in order to allow the analysis of the signal's variability associated exclusively with autonomic control.

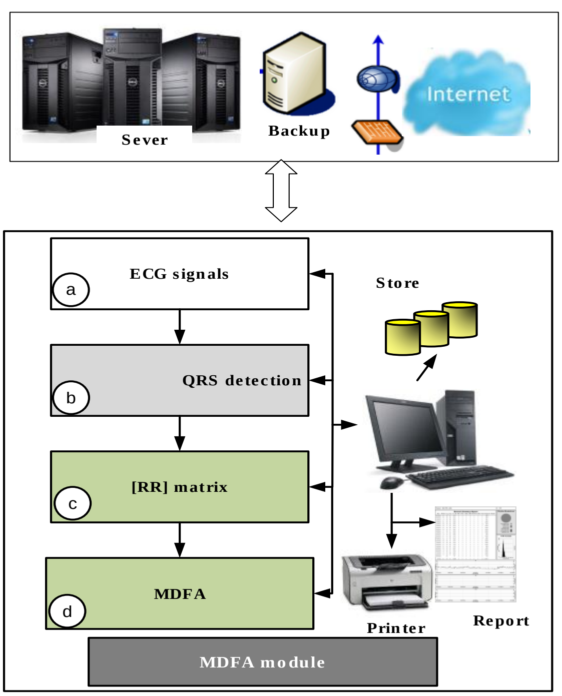

Fig. 4. Multi Fluctualtion Detrended Analysis

We made some improvements to DFA transformation method to generate a sequence of values we DFA under the 20-minute interval or heart rate in 1000. This does not affect the calculation of the DFA components but create more value from 1 DFA data matrix ECG RR only.

D. Database

The MIT-BIH Arrhythmia database was used to evaluate the proposed data compression and modulation schemes. In this standard database, the ECG signals were digitized through sampling at 360 Hz with 11-bit resolution. The first 10000 samples of 10 MIT-BIH records have been tested. After data acquisition will be carried through the separation of the QRS complex to extract RR matrix [10]. RR Matrix of ECG wave is treated in the nonlinear domain method mainly MDFA (Multi Detrended Fluctuation Analysis). Results will be calculated and compared with the traditional method of DFA (Detrended Fluctuation Analysis). Filter the results will split about arrhythmias time low, keeping the amount of time the possibility of high arrhythmias.

III. RESULT

We have collected ECG signals, then transmitted wirelessly to a data processor. In the data processing, we analyzed the matrix RR domain under MDFA nonlinear method according to the data segment 20 minutes. The result of the calculation process MDFA will be classified according to three levels are stable, arrhythmias and arrhythmia medium high.

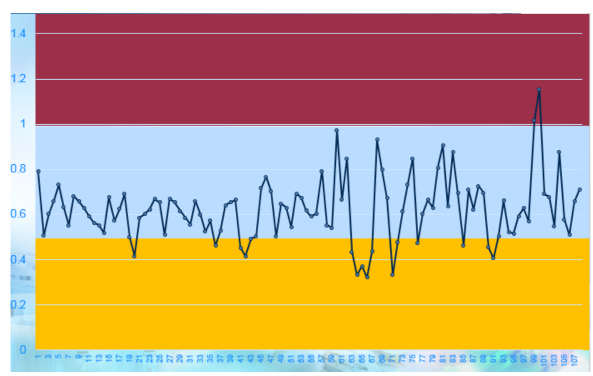

Fig. 5. Results of analysis of the degree of arrhythmia patients

Results of analysis of the degree of arrhythmia patients with follow-up time 23h53p with very high stabil-ity of 79%, the average level of arrhythmia and 3% to 18% will help doctors focus on distribution volume peri-ods occur arrhythmia respectively. This results is shown on Fig.5 and Table 2 below:

Table 2 DFA1 and DFA2 series according to the data segment 20 minutes

No	alpha	DFA1	DFA2	Meaning
1	0.5<alpha<1	**84%**	**79%**	High stability
2	0<alpha<0.5	**15%**	**3%**	Less correlated
3	1<alpha	**1%**	**18%**	Low correlation
4	alpha = 0.5	**0%**	**0%**	Noise
5	alpha = 1.0	**0%**	**0%**	Noise
6	alpha = 1.5	**0%**	**0%**	Noise

MDFA calculation process is done basically through some steps. Reduction algorithm analyzes trends on the dynamic signal analysis algorithms reducing the tendency to multi- value signal will allow limiting the downside of reducing trend analysis algorithm signal the direction of the former, while also adding some MDFA advantages:

- Track time is short enough fluctuations in the level of the heart rate associated with each other, thereby evaluate possibility of arrhythmias. Time may be short enough to allow at least 20 minutes.
- Evaluate the effectiveness and the number of beats RR minimum necessary to obtain accurate results MDFA.
- There are many values of MDFA, so evaluation is more detailed and precise.

IV. CONCLUSIONS

We have built a model of a specific system for the wireless HRV acquisition and analysis HRV arrhythmia and provide an assessment of the level of arrhythmia, arrhythmias time. The system has been tested with sample data from the MIT-BIH with good results.

The analysis of the long-term data such as HRV with DFA along with other analysis for short-term data (up to 24 hours and overnight recording) may help in providing a tool to more accurately. More long-term data are being collected to give us an opportunity to re-test the analysis and to verify the results for different physiological states.

This system is capable of development and application in Vietnam to offload hospital, physician support for arrhythmia diagnosis quickly and accurately help patients acquire ECG signals more simple, convenient more convenient.

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