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ELECTROCARDIOGRAM GENERATION SOFTWARE FOR TESTING OF PARAMETER EXTRACTION ALGORITHMS

Abstract

Fast and automated ECG diagnosis is of great benefit for treatment of cardiovascular and other conditions. The algorithms used to extract parameters need to be precise, robust and efficient. Appropriate training and testing methods for such algorithms need to be implemented for optimal results. This paper presents a software solution for computer ECG generation and a simplified concept of testing process. All the parameters of the resulting generated signal can be tweaked and set properly. Such software can also be beneficial for training and educational use.

1. INTRODUCTION

Machine – supported diagnosis has been a hot topic ever since first computers became available. This trend has become more noticeable with the advent of IoT and interconnectivity (Rincón et al., 2009). It has become even more relevant now due to the pandemic situation preventing patients from direct interaction with

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medical staff. Introduction of widespread online diagnostics systems for various medical conditions seems to be inevitable, and these will become a key element in future healthcare systems (Surtel, Maciejewski & Maciejewska, 2013). However, local patient monitoring systems are not without their own limitations. Not all procedures are safe to be performed remotely by the patients or their family due to its invasiveness. For safety reasons, it is recommended to use mostly non – invasive devices to measure parameters potentially crucial to patient condition assessment (Karpiński, Machrowska & Maciejewski, 2019; Machrowska, Karpiński, Krakowski & Jonak, 2019; Maciejewski et al., 2014).

Electrocardiography, is one of the most commonly used method of patient examination. The procedure is simple and non – invasive, as it uses surface electrodes which need to be placed on the skin in certain points. The weak voltage on the skin surface is amplified and can be viewed on a scope directly, or sampled by and A/D converter. The signal is then processed to obtain valuable information about circulatory system. Such information is vital both in routine assessment as well as in acute, life-threatening conditions. ECG can be performed with the use of simple, cheap and light devices at home, in the field or in smaller clinics, or more advanced devices with additional functionality in hospitals and various care centers.

2. ECG BASICS

Heart is an organ composed of muscle tissue and is located to the left of the sternum. It can be divided into left and right ventricle and left and right atrium. These chambers are separated by valves. In healthy individuals an electric impulse is generated in the sinoaortal node, than it travels to the atrioventricular node and to two bundles of His. This conductive cycle causes atrial contractions, followed by ventricle contraction and depolarization (Reisner, Clifford & Mark, 2006). Blood is being pumped to the lungs and the rest of the body. The electrical change can be visualized by a vector of electric potential that changes in time. It is possible to measure the electrical activity of the heart using specialized low voltage amplifiers. The resulting signal carries significant information that can be used to diagnose various heart conditions. It can be divided into waves, segments, intervals and complexes (Waechter, 2012).

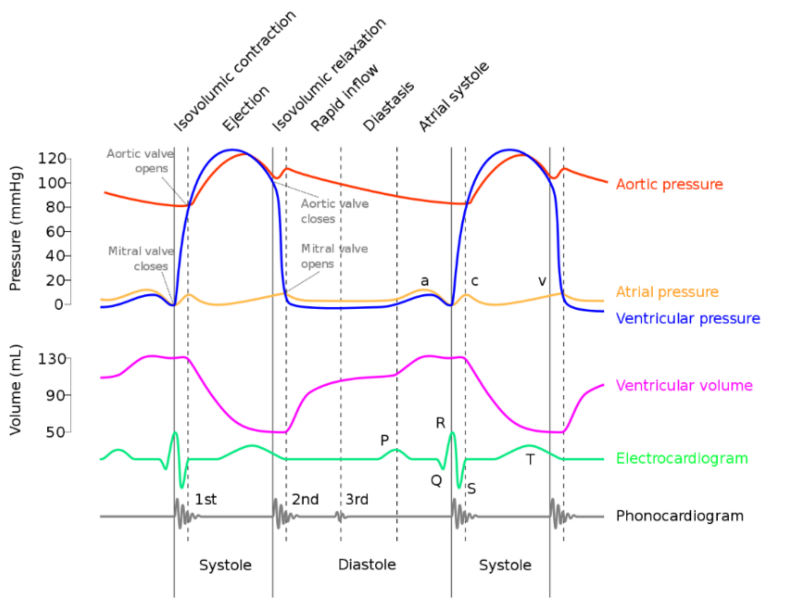

Fig. 1. Wiggers diagram – the diagram shows the aortic, atrial and ventricular pressure and the ventricular volume in relation to the ECG signal

The figure 1 (Xavax, 2016) presents changes in parameters during heart cycles. During diastole aortic pressure decreases and blood flows into the ventricles. When electrical activity forces the muscles to contract the ventricular pressure increases and blood is pumped from the heart to the system.

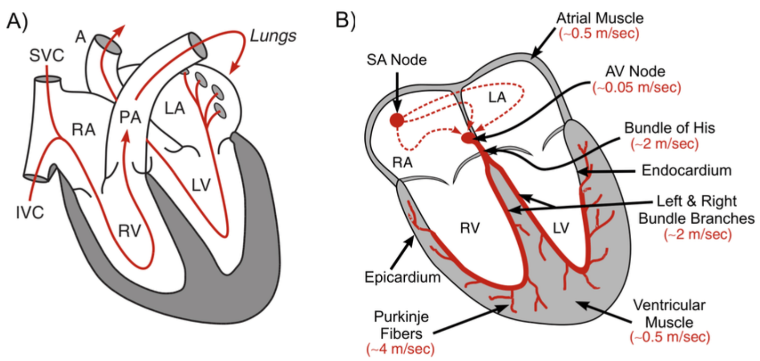

Fig. 2. Blood flow(A) and electrical activity (B) of the heart

Figure 2 (Costa, 2016) presents the direction of blood flow and electrical activity of the heart. Electrical pulse is generated in the sinoatrial node. The potential wave then travels to the rest of the heart causing contraction of muscles.

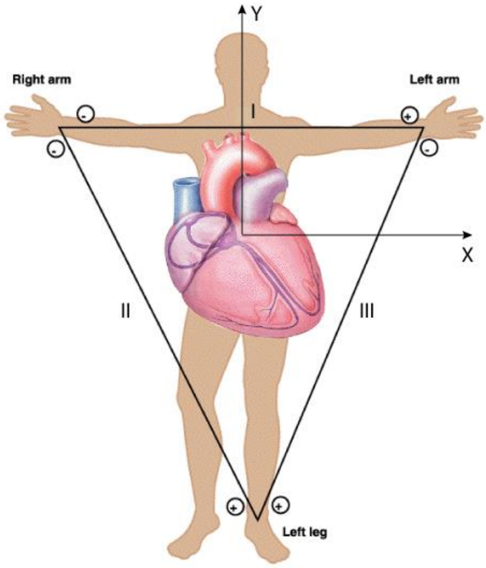

Fig. 3. Electrode placement during three lead ECG according to the Einthoven triangle (Burhan, 2011)

The figure above presents basic method for ECG electrode placement. The electrodes can be placed on arms and left leg or on torso and abdomen. Improper placement, inadequate skin preparation and damaged cabling are frequent causes of errors during procedure. These errors can result in significant artifacts or even make the signal unusable.

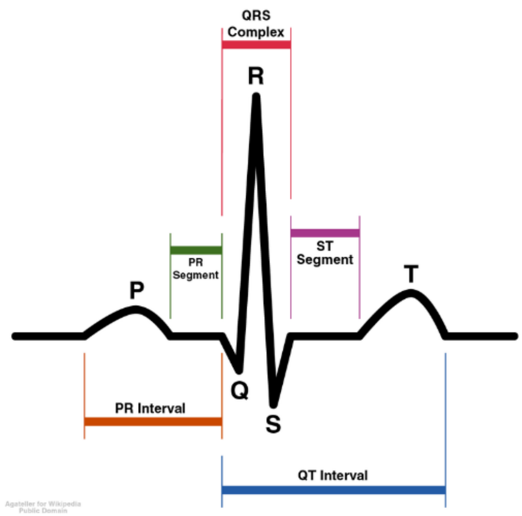

Fig. 4. Time parameters of the ECG signal commonly used for diagnosis

During ECG signal processing it is important to extract the following parameters (Luthra, 2007):

- presence of P and T waves and QRS complex in the proper order
- position, duration and amplitude of P and T waves and QRS complex,
- duration of the PR and QT intervals,
- duration of the PR and ST segments,
- length of the heart cycle, commonly calculated as time before consecutive QRS complexes,
- variability of the previously mentioned parameters.

Abnormalities in values of these parameters can be directly tied to various conditions, like arrythmias, fluttering, branch blocks, abnormal heart positioning etc. For example, changes can be caused by electrolytic imbalance, drugs, hyper- and hypothermia, anxiety and overall nervous system condition.

3. ECG DIAGNOSIS AND CLASSIFICATION

Classical ECG diagnostics is based on expert knowledge and manual signal analysis (Waechter, 2012). It is prone to human errors and the results are often presented using descriptive language, like "slightly raised", "delayed" etc., which makes it difficult for later use the data in comparative study (Maciejewski, 2019). Nowadays, it is a common practice to include computer aided diagnosis methods into the decision process (Omiotek, 2017; Rehman, Mustafa & Israr, 2013). By basing the decision on a large set of predetermined rules and cases in the database it is possible to positively influence the overall process by helping or hinting the specialist (Omiotek, Dzierżak & Uhlig, 2019).

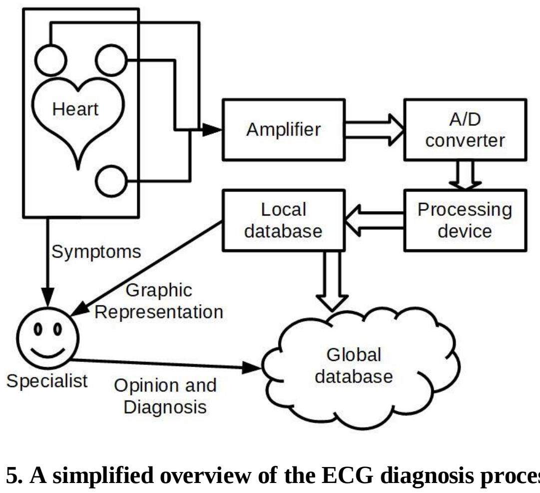

Fig. 5. A simplified overview of the ECG diagnosis process

Computer aided ECG diagnosis is based on a set of steps. These include:

- data acquisition using a sensor or a bank of sensors,
- signal preprocessing including filtration and denoising,
- feature extraction using chosen algorithms,
- classification and comparison with available knowledge base,
- presenting diagnosis.

Each step is complex in it is own way (Boulakia, Cazeau, Fernández, Gerbeau & Zemzemi, 2010). Various errors can be made during acquisition due to improper electrode placement, electronical malfunctions and data recording (Barill & SlikkStat Learning Inc., 2012). Filtration and denoising can be challenging when significant biological or technical artifacts are present in the signal (Rehman, Mustafa & Israr, 2013). Due to these factors it is sometimes hard to extract features and perform classification. These artifacts include signal drift, electrical activity of skeletal and respiratory muscles, changes in voltage due to varying skin impedance, power line interference, quantization noise etc (Bronzino, 2000; Clifford, Azuaje & Mcsharry, 2006). Filtration can be performed using, classical filters and FFT or wavelet methods (Ławicki & Zhirnova, 2015). During this process certain frequencies like 50 or 60Hz, which correspond with power line interference, need to be filtered out (Bronzino, 2000), although improper filter selection can lead to loss of sharp inflections needed to adequately process the QRS complex.

Feature extraction is usually performed in steps (Zhou, Hou & Zuo, 2009). Firstly, the position of the QRS complex is determined using various methods (Bronzino, 2000; Pan & Tompkins, 1985). Afterwards, positions of P and T waves are calculated. Lastly, durations and time intervals are estimated. Especially the last step can be hard, as the waves often are lacking a significant detectable inflection point in the beginning and end of the wave. After that it is necessary to determine parameter variability between consecutive heart cycles. In some cases when the condition presents itself randomly and it's occurrence is separated by long intervals of normal heart function it is necessary to perform long term analysis. Various acute heart conditions result in significant electrical activity variations, which in turn presents a real challenge for the designers of algorithms for ECG processing. Errors in QRS position detection are the most meaningful, as it is often used as a reference point in further analysis (Maciejewski & Dzida, 2017). Typical approaches use:

- filter banks,
- thresholding,
- polynomial estimation,
- frequency analysis,
- state machines,
- mixture of the above.

More sophisticated and complex software can combine several approaches or determine the best approach for each individual case.

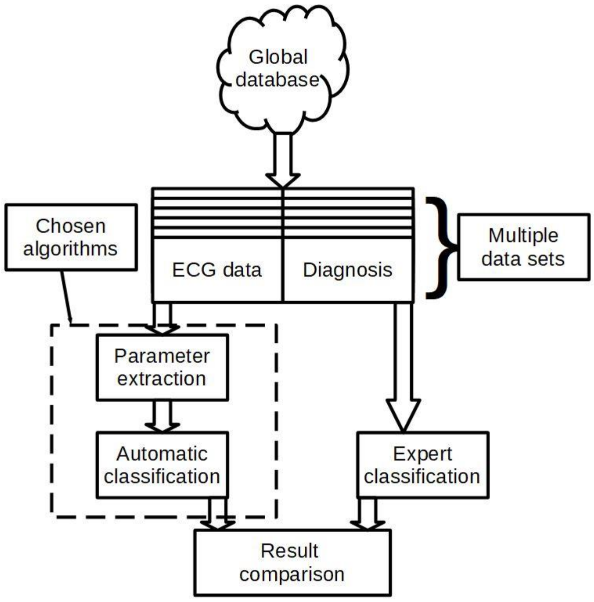

Fig. 6. Computer aided diagnosis process.

4. ECG GENERATION SOFTWARE

As previously shown, ECG analysis is a complex process. Multiple factors can result in improper results. It is possible to access vast, free databases containing ECG signals obtained from both healthy individuals and patients suffering from various cardiacconditions. This data usually has been processed and analyzed by a specialist, and is accompanied by diagnostic data. All mentioned above facts account for simplicity of ECG processing algorithms designing and testing. This process, however, can be improved.

Let’s consider a situation, when one has to determine robustness of a method while processing a noisy signal. It is necessary to check the method’s performance for multiple SNR(Signal to Noise Ratio). One has to perform these steps:

1. Choose a set of data as a basis for algorithm testing.
2. Extract ECG parameters and use them as reference points.
3. Apply noise to the signal.
4. Extract parameters and compare them with reference points.
5. Repeat until all values of SNR are tested.

A lot depends on the first two steps. It is not possible to compile a data set spanning all probable cases with varying heart rate or amplitudes and lengths of waves and QRS complex. Creating robust and accurate extraction algorithms requires testing them in as many cases as possible. This is where ECG generation software comes in.

The purpose of this type of application is generating ECG signals on demand based on input parameters. In this example a Java application was created. The software has the following functionalities:

1. Reading from an input file containing a set of parameters for further ECG generation. These include amplitudes and lengths of waves and lengths of pauses between them. Additionally, it is possible to include a randomness factor for each parameter. It is possible to generate signals corresponding to a chosen number of heart cycles.
2. Generating the signal based on the input file. The signal is constructed from exponential functions and linear segments.
3. Generating a .csv file containing information about the values of parameters for every heart cycle separately. It is necessary to save this information when randomness factor was introduced. This is the main advantage of this proposed approach.

Having access to information corresponding to each heart cycle means, that it is possible to directly compare the results from the ECG processing algorithm under test with actual values. Generating very long signals with multiple heart cycles and introducing randomness results in large sets of input data. It is also easy to automate robustness tests by introducing additional noise of chosen type and amplitude.

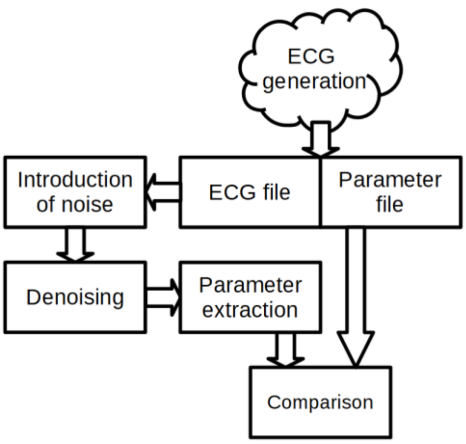

Fig. 7. Testing parameter extraction methods using ECG generation software

Additionally, it is possible to prepare a set of input parameters for various heart conditions like tachycardia, bradycardia etc. The tool is being used in the teaching process of biomedical engineering students at Lublin Institute of Technology, Poland.

Sample signals generated by the software are presented in the figures below, with additional markers corresponding to input parameters.

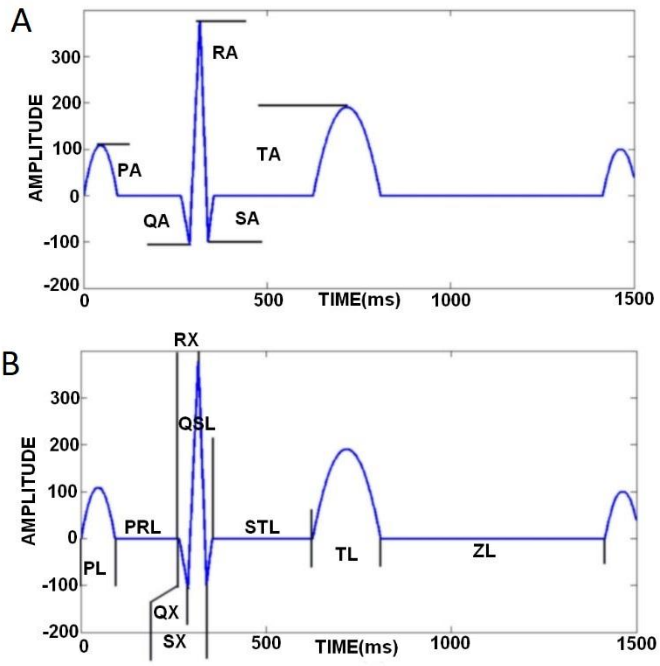

Fig. 8. Input parameters used by the software – both amplitude parameters (A) and time parameters (B) are used

5. FUTURE RESEARCH AND DEVELOPMENT

The software presented in this paper can be improved in many ways. Firstly, introduction of a proper GUI with parameter input windows and on-line heart cycle visualization will make it more intuitive to use by students and staff. Simpler saving and loading of parameter files will be introduced. Furthermore, an inbuilt database of various sets of parameters corresponding to heart conditions will be designed and implemented. Afterwards, methods for introduction of noise and artifacts will be included. Lastly, this software may become available to download in Java version or Python after porting.

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