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ALGORITHM FOR AUTOMATIC RECOGNITION OF CARDIAC ARRHYTHMIAS

Abstract. Problem statement: Cardiovascular diseases currently remain one of the leading causes of death. It is important to monitor the state of the cardiovascular system in early stages of pathology in order to diagnose these diseases in a timely manner. A special place is occupied by various arrhythmias among diseases of the cardiovascular system. The most common ones of various arrhythmias are extrasystoles. Ventricular extrasystoles are considered the most life-threatening among extrasystoles. In order to diagnose ventricular extrasystoles at an early stage of their development, it is necessary to process and analyze large amounts of electrocardiographic data. In this regard, the development and software implementation of algorithms for automatic recognition of ventricular arrhythmias based on electrocardiographic data through modern computer technologies is an urgent task. Work objective is developing an algorithm for automatic recognition of ventricular arrhythmias and its software implementation. Results: An algorithm for automatic recognition of ventricular extrasystoles, which is characterized by simplicity of implementation and minimal requirements for computing resources, has been developed. At the same time, high values of sensitivity and specificity are maintained for ECG signals with single ventricular extrasystoles. The algorithm is implemented in the LabVIEW software environment and tested using ECG files taken from international databases on cardiac arrhythmias, as well as using stimulated ECG signal models. Practical significance: The developed algorithm can be used in automatic processing and analysis of long-term ECG recordings and recognition of ventricular arrhythmias.

Keywords: Electrocardiographic signal, arrhythmia, ventricular extrasystole, phase space, phase portrait, RR intervals, LabVIEW software, heart rate.

Introduction

Currently, cardiovascular disease ranks first among all diseases in terms of danger to human life. The most common symptoms, precursors of cardiovascular diseases are cardiac arrhythmias - heart rhythm disturbances. Characteristic features of arrhythmias are determined based on the results of the analysis of heart rate variability (HRV). Heart rhythm disturbances that occur abnormally related to the main heart rhythm and manifest as excitation of the heart as a whole or its individual parts are called extrasystoles.

The cause of extrasystole is explained by the presence of active heterotopic foci that generate electrical impulses of sufficient power that disrupt the main sinus rhythm. Depending on the localization in the heart, there are supraventricular extrasystoles: sinus, atrial, atrioventricular and ventricular extrasystoles. The distinction between ventricular extrasystoles and supraventricular extrasystoles should be considered very important, since some medications for the treatment of supraventricular extrasystoles can worsen the clinical condition if the rhythm is ventricular.

Ventricular extrasystole is the most common cardiac arrhythmia.

The prevalence of arrhythmias directly depends on age and the presence of heart pathology. Ventricular extrasystole is an alarm signal in patients with cardiomyopathies, valvular heart disease, severe myocardial ischemia, as well as with cases of sudden death in a family history [1].

Timely diagnosis of cardiac arrhythmias can help reduce the risk of adverse outcomes for patients with cardiovascular disease. One of the main directions in the development of modern electrocardiography is the expansion in the use of automated analysis of ECG signals. Automated ECG analysis enables cardiologists to more accurately determine the parameters of

electrocardiographic signals, objectively and quickly assess the state of the heart, and increases the probability of making a right decision about the patient and recommendations for his treatment in the future. Recently, there has been a significant increase in the number of algorithms assigned for automated ECG analysis, and at the same time, the expansion in the scope of their application. This is due to two main factors. First, unfortunately, the number of cardiovascular diseases is increasing, most of which are caused by arrhythmias. Secondly, a significant increase in the capabilities, power and speed of computer technologies, which makes it possible to implement even mathematically complex signal processing algorithms without fundamental difficulties, including in real time.

Goal setting and research objectives

Cardiac arrhythmias are usually diagnosed by electrocardiogram (more reliably by Holter ECG monitoring) based on P, QRS, and T wave characteristics of ECG. Reliable recognition of these complex ECG characteristics, which are specifically associated with cardiac arrhythmias, requires considerable competence and training of medical specialists. However, processing such a large amount of information and making a correct diagnosis in the limited time allotted to the patient is a difficult task even for experienced doctors. The problem of detection and recognition of arrhythmias can be effectively solved using computer algorithms for automatic diagnosis of arrhythmias. Based on these considerations, the objective of this work is to develop an algorithm for automatic recognition of ventricular arrhythmias and software implementation of this algorithm.

The question of accurately determining the boundaries of QRS complexes and the allocation of R peaks in ECG signals is of fundamental importance in the diag-

nosis of arrhythmias and in the recognition of signals in clinical manifestations in general.

Existing methods for detecting QRS complexes can be divided into two large groups: the first group includes high-precision methods designed for basic clinical examinations using several divisions; the second group includes methods used in mobile electrocardiographic devices allowing real-time analysis and are intended for patients with cardiac failure. Automating the classification of arrhythmias by ECG is very important for making a quick and objective decision about the class of arrhythmia.

The main requirements for an automated system are not the complexity of the algorithm, making a quick decision and less memory.

Research methods and materials

Generally, the algorithm used to automatically classify arrhythmias consists of three steps: preliminary processing, extraction and classification of feature. Preliminary processing of recorded ECG signals is performed to remove noise that degrades classifier performance, such as baseline deviation, motion artifact, power line interference, and high frequency noise.

Preliminary processing was carried out on the basis of wavelet transform. Wavelet analysis remains a popular technique for both filtering and extraction of feature.

Extractable features of ECG include:

a) temporal features of palpitation, such as P-Q interval, QRS interval, S-T interval, Q-R interval, R-S interval, and R-R interval between adjacent cardiac contractions,

b) amplitude characteristics, such as amplitudespeak of P, Q, R, S and T characteristics based on wavelet transform, at different levels of decomposition.

A comparative analysis of the main technological methods for constructing algorithms to detect QRS complexes in ECG signals was considered at different times in numerous studies, for example, in [2-5].

A number of approaches have been proposed for the detection of QRS complexes, such as:

wavelet transforms [5, 7],

algorithms from the field of artificial neural networks [8, 9],

genetic algorithms [10],

filter banks [11],

as well as heuristic methods based on non-linear transformations of ECG elements [12].

Experimental results

Today, there are many methods for detecting normal and pathological QRS complexes [5,13-18], which practically represent improvement of previously known methods.

These improvements are aimed at eliminating various interferences, applying various transformations for reliable detection and recognition of arrhythmias. However, the problem associated with unpredictability of the rhythm behavior even in one patient still remains open and raises the question of improving the algorithms for identifying QRS complexes and creating algorithms that

are weakly dependent on a particular patient. For that purpose, in contrast to the existing algorithms, which are mainly based on a comparative analysis of differences in RR intervals with their averaged values, we have proposed an algorithm based on the analysis of the ratios of these intervals for the recognition of arrhythmias.

When interpreting the results of Holter monitoring, the followings are realized under the general name "high-grade ventricular arrhythmias" [1]:

1) single extrasystoles;

2) polytopic extrasystoles;

3) extrasystoles of type <<R to T>>;

4) ≥ 2 consecutive ventricular extrasystoles.

The article proposes an algorithm for recognizing single ventricular extrasystoles.

As it is known, at the time of rhythm disturbances, the change in RR interval is $\geq 10\%$.

Based on this, it can be said that in the case of a normal rhythm, the ratio of two adjacent intervals ΔR_{i-1} and ΔR_i should satisfy the condition:

$$0,9 \leq \alpha_i \leq 1,0, \quad (1)$$

where

$$\alpha_i = \frac{\Delta R_i}{\Delta R_{i-1}}.$$

In the case of a normal rhythm, regardless of the absolute lengths of adjacent intervals, condition (1) should be preserved (weakly depends on a specific healthy rhythm). So, the essence of the algorithm proposed by us is as follows:

1) the investigated file of ECG data is loaded (or registered online);

2) amplitudes and localizations of R peaks are distinguished;

3) the sequence of lengths of RR intervals is determined

$$\{\Delta R_i = \Delta R_i - \Delta R_{i-1}\};$$

4) according to the obtained series of sequences of RR interval lengths, a new sequence of such a_i elements, which are defined as the ratio of adjacent RR intervals, is determined:

$$\left\{ \alpha_i = \frac{\Delta R_i}{\Delta R_{i-1}} \right\}.$$

5) according to the number of a_i values satisfying conditions $a_i \leq 0,9$ or $a_i \geq 1$, the number of extrasystoles or arrhythmias is calculated.

These conditions correspond to the appearance of pathological intervals, i.e., change in the frequency of contractions is not less than 10%.

If the number of a_k values corresponding to pathological intervals is exactly n_k , then the number of arrhythmias (extrasystoles) n_e , will be determined by formula

$$n_e = \frac{n_k}{3}.$$

As it is seen from Fig. 1, this ratio follows from ECG with a single ventricular extrasystole.

6) according to the number of rhythm disturbances, diagnostic parameters (sensitivity, specificity) and temporal localization of extrasystoles are determined. This algorithm was implemented in LabVIEW 2014 software environment.

Fig. 2 shows the front panel of the program. The program consists of three subroutines: reading a file, generating cardiointervalogram (CIG), signal analysis.

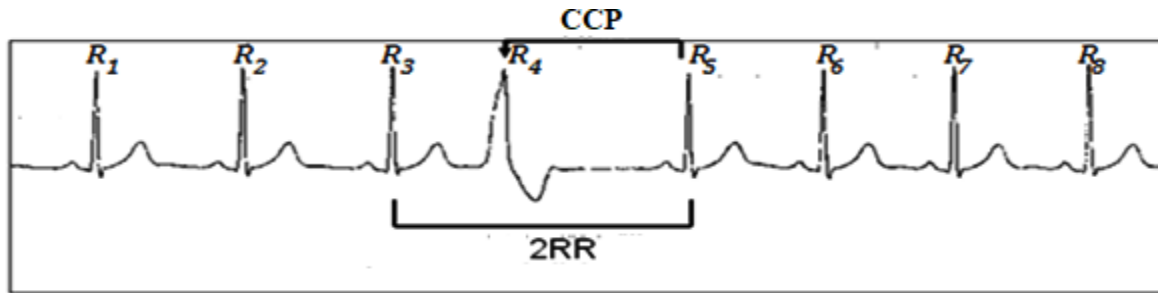


Fig. 1. Single ventricular extrasystole (indicated by an arrow). CCP is a complete compensatory pause. 2RR - two normal cardiac cycles. (Holter monitoring ECG recording) [19]

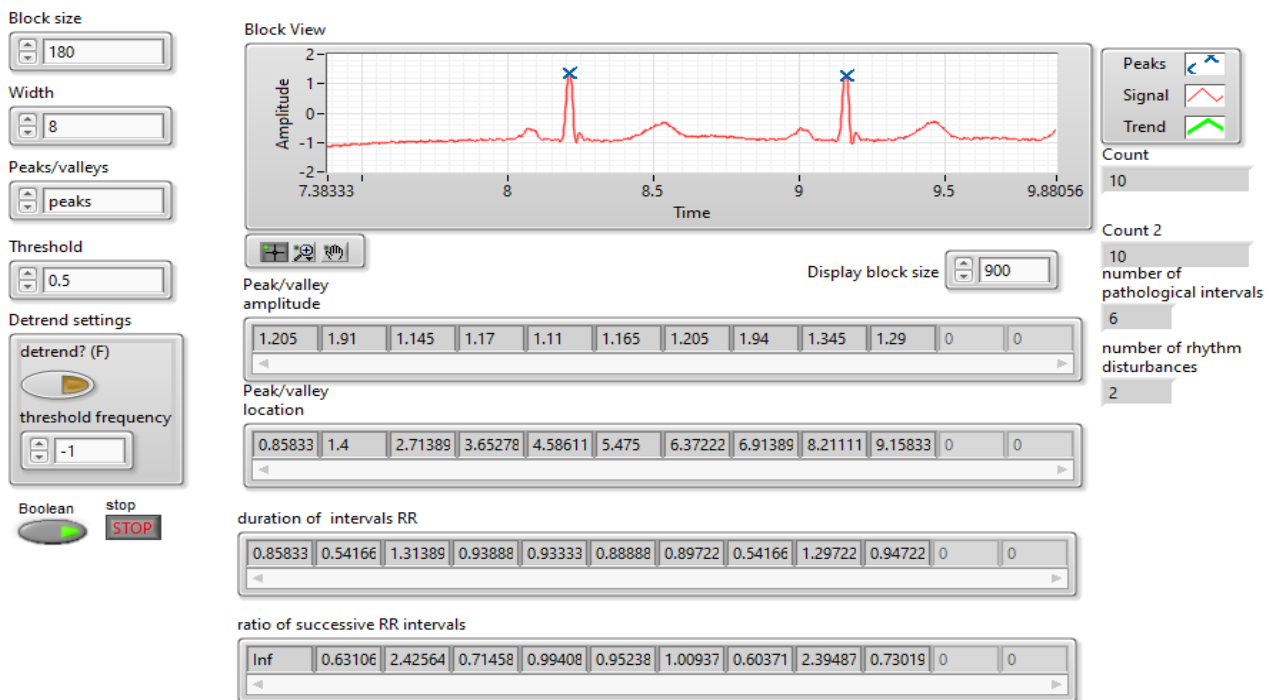


Fig. 2. Program for detecting arrhythmias in the environment of LabVIEW

The file is read using the function of *Read Biosignal Express VI*.

Configuration virtual instrument of *Read Biosignal Express VI* allows to access the folder where the file under study is available, cut the desired part from the file, select the desired lead, present the file as a sequence of reports (Waveform Values).

CIG formation subroutine was implemented using the function of *WA Online Multiscale Peak Detection VI*, which allows to identify the peaks of R and their localization in real time based on wavelet analysis.

Using the obtained CIG, an analysis of HRV and recognition of arrhythmias was carried out.

Discussion of the results

In order to test the performance of the proposed algorithm, real signals were used from the annotated

international databases of Physio net site [20] - from the database of Massachusetts Institute of Technology (MIT-BIH), in accordance with the recommendations of AAMI. EC57:2012 [21].

Electrocardiography signals from this database are considered today as a generally recognized standard for testing software tools designed for cardiology applications.

MIT-BIH Arrhythmia Database contains 48 half-hour extracts from dual-channel ambulatory ECG recordings.

Characteristics of the signals of this base are:
 the number of leads - 2 (II standard, V1),
 sampling frequency - 360 Hz;
 ADC resolution - 11 bits.

In addition, stimulated models of ECG signals were also used to test the program.

Table 1 presents the results of testing the program using fragments of various lengths of 119.hea file, taken from MIT-BIH database.

The results of testing the program, as it is seen from tables 1 and 2, gives satisfactory results.

However, further research showed that the program for signals with sinus rhythm and single ventricular extrasystoles gives high results, the reliability of

detecting pathological QRS complexes in which is 97-98%.

In order to recognize more complex extrasystoles, this algorithm should be improved, taking into account the structural features of extrasystoles.

Table 2 shows the results of testing the program for fragment:

00.00.00-00.00.10 sec of file 119.hea.

Table 1 – Results of testing the program

| Length of signal fragment | Number of complexes | Real number of extrasystoles | The number of extrasystoles detected by the program | Detection of error |
|---------------------------|---------------------|------------------------------|---|--------------------|
| 00.00.00- 00.00.10 sec | 10 | 2 | 2 | 0 |
| 00.00.00- 00.00.20 sec | 21 | 3 | 4 | +1 |
| 00.00.00- 00.00.50 sec | 55 | 14 | 12 | -2 |
| 00.00.00- 00.00.100 sec | 108 | 25 | 21 | -4 |

Table 2 – The results of testing the program for fragment 00.00.00- 00.00.10 sec of file 119.hea

| Localization of observed peaks of R, sec | Length of RR intervals $\{\Delta R_i = R_i - R_{i-1}\}$ | Ratio of adjacent RR intervals: $\{a_i = \Delta R_i / \Delta R_{i-1}\}$ | Belonging to pathological interval | Number of rhythm disturbances (extrasystoles) |
|--|---|---|------------------------------------|---|
| 0.858333 | 0.858333 | | | 2 |
| 1.4 | 0.541667 | 0.631068 | yes | |
| 2.71389 | 1.31389 | 2.42564 | no | |
| 3.65278 | 0.938889 | 0.714588 | yes | |
| 4.58611 | 0.933333 | 0.994083 | no | |
| 5.475 | 0.888889 | 0.952381 | no | |
| 6.37222 | 0.897222 | 1.00937 | no | |
| 6.91389 | 0.541667 | 0.603715 | yes | |
| 8.21111 | 1.29722 | 2.39487 | yes | |
| 9.15833 | 0.947222 | 0.730193 | yes | |

Conclusions

An algorithm was developed to perform ECG signal processing procedures and detect QRS complex in accordance with the requirements of AAMI EC57:2012 documents [21] for reliable identification of arrhythmias. The proposed algorithm for recognition of arrhythmias (ventricular extrasystoles) is characterized by simplicity of implementation and minimal requirements for

computing resources, while maintaining high values of sensitivity and specificity for ECG signals with sinus rhythm and single ventricular extrasystoles.

The developed program was tested using ECG signal of 119.hea from MIT BIH database [20] as well as models of stimulated ECG signals in LabVIEW environment.

The results obtained during the processing and analysis of ECG files taken from databases [20, 22] (di-

agnostic features of which were known in advance) with space” and “HRV analysis system”) implemented in both systems (“ECG signal analysis system in phase LabVIEW environment confirm their adequacy.

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Received (Надійшла) 14.02.2023

Accepted for publication (Прийнята до друку) 26.04.2023

Алгоритм автоматичного розпізнавання порушень ритму серця

Самедова Шафаг

Анотація. Постановка проблеми: Серцево-судинні захворювання нині залишаються однією з провідних причин смертності. Важливо стежити за станом серцево-судинної системи на ранніх стадіях патології, щоб своєчасно діагностувати ці захворювання. Особливе місце серед захворювань серцево-судинної системи посідають різні аритмії. Найбільш частими з різних аритмій є екстрасистоли. Шлуночкові екстрасистоли вважаються найбільш небезпечними для життя екстрасистолами. Для діагностики шлуночкових екстрасистол на ранній стадії їх розвитку потрібна обробка та аналіз великих обсягів електрокардіографічних даних. У зв'язку з цим розробка та програмна реалізація алгоритмів автоматичного розпізнавання шлуночкових аритмій на основі даних електрокардіографії за допомогою сучасних комп'ютерних технологій є актуальним завданням. Мета роботи – розробка алгоритму автоматичного розпізнавання шлуночкових аритмій та його програмна реалізація. Результати: Розроблено алгоритм автоматичного розпізнавання шлуночкових екстрасистол, що відрізняється простотою реалізації та мінімальними вимогами до обчислювальних ресурсів. У той же час високі значення чутливості та специфічності зберігаються для сигналів ЕКГ з одиничними шлуночковими екстрасистолами. Алгоритм реалізований у програмній середовищі LabVIEW та протестований з використанням файлів ЕКГ, взятих із міжнародних баз даних за сердечними аритміями, а також із використанням моделей стимульованих сигналів ЕКГ. Практична значущість: Розроблений алгоритм може бути використаний для автоматичної обробки та аналізу тривалих записів ЕКГ та розпізнавання шлуночкових аритмій.

Ключові слова: електрокардіографічний сигнал, аритмія, шлуночкова екстрасистоля, фазовий простір, фазовий портрет, RR-інтервали, програма LabVIEW, частота серцевих скорочень.