Розроблено систему альтернативних діагностичних ознак на основі методу морфологічного аналізу біомедичних сигналів з локально зосередженими ознаками з метою надання додаткової інформації при діагностиці шлуночкової екстрасистолії. Запропоновано представлення електрокардіограми в альтернативному просторі ознак у вигляді годографа. Проаналізовано відмінності годографів для нормальної електрокардіограми та електрокардіограм з різними видами шлуночкової екстрасистолії

Ключові слова: альтернативний простір ознак, електрокардіограма, шлуночкова екстрасистолія, годограф

Разработана система альтернативных диагностических признаков на основе метода морфологического анализа биомедицинских сигналов с локально сосредоточенными признаками с целью предоставления дополнительной информации при диагностике желудочковой экстрасистолии. Предложено представление электрокардиограммы в альтернативном пространстве признаков в виде годографа. Проанализированы отличия годографов для нормальной электрокардиограммы и электрокардиограмм с различными видами желудочковой экстрасистолии

Ключевые слова: альтернативное пространство признаков, электрокардиограмма, желудочковая экстрасистолия, годограф

UDC 004.9:616.1

DOI: 10.15587/1729-4061.2016.71949

DEVELOPMENT OF ALTERNATIVE DIAGNOSTIC FEATURE SYSTEM IN THE CARDIOLOGY DECISION SUPPORT SYSTEMS

A. Povoroznyuk
Doctor of Technical Sciences, Professor*
E-mail: ai.povoroznjuk@gmail.com
A. Filatova
PhD, Associate Professor*
E-mail: filatova@gmail.com
*Department of Computer Engineering and Programming
National Technical University "Kharkiv Polytechnic Institute"
Bagaliya str., 21, Kharkiv, Ukraine, 61002

1. Introduction

Currently, the production of Ukrainian digital electrocardiographic telemetry systems has increased significantly [1, 2]. Using electrocardiographic telemetry systems, electrocardiograms (ECG) can be recorded and recorded signals can be transferred to the distant diagnostic center. For example, transtelephonic digital 12-channel electrocardiograph complex "Telecard" developed by "TREDEX Company" (Kharkov, Ukraine) deserves attention [3, 4]. In the "Telecard" complex, ECG transmission is performed through any communication channels including standard telephone lines, mobile communication channels, radio channels of any range and telephone channels of the DECT standard. ECG is encoded and transmitted in digital form, which provides guaranteed high quality of the signal and allows to diagnose any heart disease such as ischemic heart disease, myocardial infarction, various heart rhythm disorders, etc., by a cardiologist in the distant diagnostic center.

Thus, the problem of design of intelligent automated cardiac decision support systems (CDSS) which are part of the electrocardiographic telemetry systems is urgent. Creation and introduction of such systems will improve the quality of diagnosis in medical emergency rendering.

2. Analysis of previous studies and the problem statement

Traditionally, morphological ECG analysis is performed to diagnose the state of the cardiovascular system. Particularly electrocardiography is used to determine the frequency and regularity of heartbeats. Premature beats is the most common disorder of heart rhythm. Extrasystole is extraordinary excitement (and subsequent contraction) of the heart or its parts resulting from heterotopic excitation of the myocardium [5]. The peculiarity of this disease is that the extrasystoles occur randomly on the background of a large number of normal periods, which requires a long (several hours) ECG monitoring [6], while automated methods for the detection of "suspicious" periods are virtually not available. In practical work and scientific research, the main attention is focused on ventricular arrhythmia as some types of premature ventricular contractions (PVCs) can indicate the possible development of ventricular fibrillation [7, 8].

ECG is a biomedical signal (BMS) with locally concentrated features (LCF) [9]. During ECG analysis, the waves and complexes are allocated [10, 11], their amplitude and time characteristics are measured, as well as the shape of the selected structural elements is analyzed [12].

Traditionally, the BMS with LCF analysis is performed in the temporal domain with the usage of modern classification methods such as cluster analysis and pattern recognition [13, 14], neural networks [15], fuzzy clustering [16, 17]. Despite the use of different methods for classification, in their implementation, researchers face a number of common issues specific to the analysis of such a complex signal as the ECG. Most of the methods require a manual marking of the signal which is not possible for long-term ECG monitoring. Due to the high variability of ECG, the methods tuned for a particular data set can give large errors in other data sets.

In addition, these methods require a significant amount of training samples during the training phase. The process of formation of the training sample is not trivial as it is based on the user experience (cardiologist), so it is prone to errors and is costly in terms of both time and money. In case of cluster analysis, it is necessary to take into account factors such as computational costs, significant asymmetry of classes, the uncertainty of the classes number and primary partitions, as well as the variability of the signal, artifacts, etc.

Along with the traditional ECG analysis, the attempts to obtain more information by analyzing alternative features resulting, for example, from the spectral analysis in the local region [18], wavelet transform [19], etc. are conducted. As a rule, the transition to the frequency and time-frequency characteristics is associated with high computational costs, even in the case of fast calculation algorithms. Alternative features may be considered as together with conventional amplitude-time characteristics, as well as those individual. For example, the effectiveness of the phase space for the diagnosis of certain states of the cardiovascular system using ECG is shown in [2, 9]. However, the phase space does not include features of the analyzed signal; in this case, the ECG analysis using the phase space is made for the average trajectory that does not allow detecting conditions such as premature beats.

To solve the problem of morphological analysis of BMS with LCF, in [20] the authors suggested the method based on the construction of a multi-channel non-linear filter (NF). The task of this method is detection of structural elements (SE) of the given type and their localization on the useful signal. The basis of the method is the idea of transformation of BMS with LCF into a new feature space using the properties of the useful signal model. The proposed method of morphological analysis of BMS with LSP improves the accuracy of detection of structural elements of ECG on the noise background [21].

Therefore, further development of the method of the morphological analysis of BMS with LCF suggested by the authors in order to improve the quality of diagnosis of ventricular arrhythmia in the CDSS by providing additional diagnostic information obtained as a result of representation of the ECG in the new feature space is of interest.

3. The objective and tasks of the study

The objective of the research is to give alternative diagnostic features in readable graphic form for cardiologists along with the traditional presentation of ECG signal.

To achieve this objective, the following tasks should be solved:

– to develop a system of alternative diagnostic features that can be represented in a human-readable graphical form;

– to investigate the diagnostic value of the system of alternative diagnostic features for premature ventricular contractions.

4. The method of morphological analysis of biomedical signals with locally concentrated features

To solve this problem, let us consider the proposed in [20] method of morphological analysis of BMS with LCF in more detail (Fig. 1).

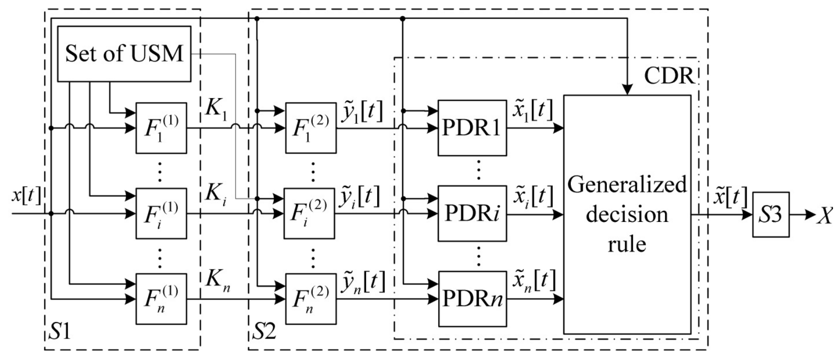


Fig. 1. Generalized scheme of morphological analysis of BMS with LCF on the basis of the non-linear filter

In step S1, in each channel corresponding transformation of the input signal $x[t]$ $(t=\overline{0;T_s-1}$, T_s – length of the input signal) is performed with consideration of the useful signal model (USM). The output of each block $F_i^{(1)}$ generates the tuple of parameters for NF (linear dimensions of the aperture, the weight function of the filter, the prototype of SE of the given class):

$$K_i=\langle x_0[t],P_i,f_i(x[t],P_i)\rangle,$$

where $x_0[t]$ $(t=\overline{0;T_0-1})$ – reference signal (the prototype of SE of the given class); $T_0 << T_s$ – length of the prototype; P_i – set of parameters for the i-th channel; $f_i(x[t],P_i)$ – the i-th transformation function of the signal $x[t]$ within the aperture.

The linear size of the aperture is defined by a linear dimension T_0 of the prototype $x_0[t]$ of the given structural elements on the time axis.

Step S2 is a non-linear filtering. The result of this step is finding the desired structural elements (Fig. 1). In each block $F_i^{(2)}$, the detection function $\tilde{y}_i[t]\in[0;1]$ of the i-th channel is defined as

$$\tilde{y}_i[t]=\frac{1}{1+\alpha_i D^2(\omega_i^p,\omega_i^t)}, \qquad (1)$$

where $\alpha_i\in(0;1]$ –coefficient reflecting the sensitivity to changes in structural elements of the same class due to the presence of noise and variation of parameters;

$$D^2(\omega_i^p,\omega_i^t)=\sum_{j=1}^{Na_i}(y_{ij}^p-y_{ij}^t)^2$$

is square of the distance between the prototype ω_i^p of the structural elements and the current object ω_i^t within the aperture;

$$y_{ij}^p=f_i(x_0[t],P_i),\quad y_{ij}^t=f_i(x[t],P_i)$$

are coordinates of the objects ω_i^p and ω_i^t respectively; $\alpha_i, Na_i, t\in P_i$.

Detection of the structural elements of the given type in the i-th channel is performed using the private decision rule (PDRi) based on detection function $\tilde{y}_i[t]$ [22, 23]:

$$\tilde{x}_i[t] = \begin{cases} x[t] \ \forall t \in [t_{ie}; t_{ie} + T_0] & \text{if } \tilde{y}_i[t_{ie}] > Pd_i; \\ x^0 & \text{in other cases,} \end{cases} \quad (2)$$

where $\tilde{x}_i[t]$ – private filter response; t_{ie} – point of local maximum of the function $\tilde{y}_i[t]$ that it is $\tilde{y}_i[t_{ie}] \geq \tilde{y}_i[t]$ $\forall t \in \dot{\mathbf{M}}(t_{ie})$; $\tilde{y}_i[\cdot]$ – detection function of mode (1) of the i-th channel; $\dot{\mathbf{M}}(t_{ie}) = \mathbf{M}(t_{ie}) \setminus \{t_{ie}\}$ – deleted neighborhood of the point t_{ie}; $\mathbf{M}(t_{ie})$ – neighborhood of the point t_{ie}; e – index of local maximum; Pd_i – threshold of PDRi; $x^0 = \text{const}$ – constant which determines the signal level corresponding to the absence of SEs of the given type in the current signal fragment (for example, ECG isoline level).

Then private decision rules are combined into collective of decision rules (CDR), the result of this union is a signal $\tilde{x}[t]$ containing structural elements of the given class.

In step S3, the characteristics of found structural elements of the signal $\tilde{x}[t]$ are calculated. These characteristics are the components of the set X. The components of the set X are the traditional diagnostic features that are used to diagnose the state of the cardiovascular system by ECG.

5. Development of alternative diagnostic features system

According to a specific decision rule (2), not all the objects ω_i^t are subjected to the classification but only the objects $\tilde{\omega}_i^e$ for which the detection function $\tilde{y}_i[t]$ has local maximums ($\{\tilde{\omega}_i^e\} \subset \{\omega_i^t\}$). I. e., each classified object $\tilde{\omega}_i^e$ is the fragment of signal $x[t]$ of length T_0 which starts at the point t_{ie}.

In its turn, $\{\tilde{\omega}_i^e\} = \Omega_1 \cup \Omega_2$, $\Omega_1 \cap \Omega_2 = \varnothing$, where Ω_1, Ω_2 are sets of the desired structural elements and all other objects respectively. In addition, each object $\tilde{\omega}_i^e$ can be described as in the original feature space by amplitudes $x[t]$ of said signal fragment and in an alternative feature space by coordinates $\tilde{y}_{ij}^e$ calculated using the functions $f_i(x[t], P_i)$. It should be noted that only objects of the set Ω_1 coincide with the structural elements accepted in medical practice. The objects of the set Ω_2 are abstract and their properties are not analyzed in the conventional diagnosis of the cardiovascular system by ECG. However, since in step S1 (Fig. 1) the input signal transformation is performed by the useful signal model then in the new feature space the structural elements are described by diagnostic features adapted to the useful signal model and maximally taking into account the properties of considered BMS with LCF. Therefore, the relative position of objects of the sets Ω_1 and Ω_2 in an alternate feature space is useful to consider in order obtaining additional diagnostic information.

Most clearly the relative position of objects of the sets Ω_1 and Ω_2 could be visualized in graphical form. It is necessary that the number of coordinates is $Na_i \leq 3$ in the alternative space, and the coordinate values $\tilde{y}_{ij}^e$ should be normalized.

To normalize the coordinates of objects $\tilde{\omega}_i^e$, let us use the properties of detection function (1). The normalized distance $D'(\omega_i^p, \omega_i^t) \in [0;1]$ between objects ω_i^p and ω_i^t can be determined using detection functions $\tilde{y}_i[t]$ as follows:

$$D'(\omega_i^p, \omega_i^t) = \sqrt{1 - \tilde{y}_i[t]} = \sqrt{1 - \frac{1}{1 + \alpha_i D^2(\omega_i^p, \omega_i^t)}} =$$
$$= D(\omega_i^p, \omega_i^t)\sqrt{\frac{\alpha_i}{1 + \alpha_i D^2(\omega_i^p, \omega_i^t)}} = D(\omega_i^p, \omega_i^t)\sqrt{\alpha_i \tilde{y}_i[t]}. \quad (3)$$

Then, taking into account the expression (3), the alternative diagnostic features $\tilde{y}_{ij}^{\prime e}$ normalized and centered relative to the prototype ω_i^p for the i-th channel are determined with the following expression:

$$\tilde{y}_{ij}^{\prime e} = (y_{ij}^p - \tilde{y}_{ij}^e)\sqrt{\alpha_i \tilde{y}_i[t]}, \quad (4)$$

where $\tilde{y}_{ij}^{\prime e}$, $\tilde{y}_{ij}^e$ – normalized and not normalized coordinates of objects ω_i^p and ω_i^t in the alternative feature space.

It's obvious that $\tilde{y}_{ij}^{\prime e} \in [0;1]$ and $\tilde{y}_{ij}^{\prime e} = 0$ if the object $\tilde{\omega}_i^e$ coincides with the prototype ω_i^p, i. e. $y_{ij}^p = \tilde{y}_{ij}^e$ $\forall j = \overline{1, Na}$. Then, the more the object ω_i^p is similar to the prototype ω_i^p in an alternative feature space, the closer this object will be located to the origin. And the most diverse objects will be located at the boundary of the unit circle.

6. Visualization of QRS complexes in the alternative feature space

To present the ECG in proposed alternative feature space (AFS), the QRS complex of lead I of normal ECG averaged as per 50 periods was selected as a prototype. Morphological analysis was performed using a single channel of the designed NF (Fig. 1), so the following description of experiments index *i* is omitted. The finite difference of the first order was used as the transformation function $f(x[t], P)$ in order to describe the prototype ω^p in AFS [23]:

$$f(x[t], P) = \frac{x[t_{k+1}] - x[t_k]}{t_{k+1} - t_k}, \quad (5)$$

where $t_k \in P$ – indices of reference points between which the finite difference is calculated.

Left and right slopes of the QRS complex are described by the transformation function (5) (Fig. 2 shows corresponding sections between peaks of the Q, R and R, S waves), so the number of coordinates is $Na = 2$.

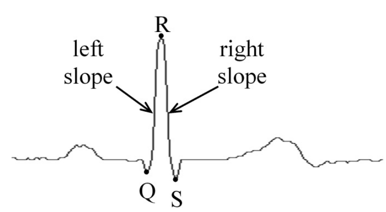
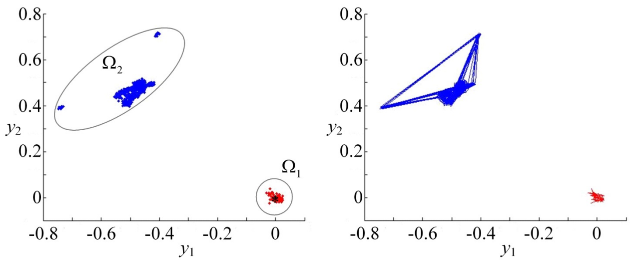


Fig. 2. A typical QRS complex of lead I of normal ECG

As a result of the morphological analysis of the QRS complexes of normal ECG is visualized in the AFS as two compact clusters (Fig. 3, *a*). In addition, the authors propose another presentation of the objects in AFS as the hodograph, which is constructed by connecting all the objects $\tilde{\omega}_i^e$ in AFS. Let us call this hodograph as ECG-hodograph (Fig. 3, *b*).

In Figs. 3–10, the objects of the set Ω_1 are marked in red, and the objects of the set Ω_2 – in blue. Since according to (4) normalization of coordinates of objects $\tilde{\omega}_i^e$ is performed relative to the prototype ω^p, the object ω^p is always located at the origin of AFS.



a *b*

Fig. 3. Visualization of normal ECG in AFS: *a* – the location of the object relative to ω^p (marked *); *b* – ECG-hodograph

7. Visualization of normal ECG and ECG with premature ventricular contractions in the ASF

As it was previously mentioned, the considered BMSs with LCF are quasi-periodic signals. The lower is the variability of heart rate and ECG structural elements (waves and complexes), the more compacted object groups should be formed in the alternative feature space. Conversely, the greater is the variability of the structural elements, the more blurry object groups will be formed in the alternative feature space.

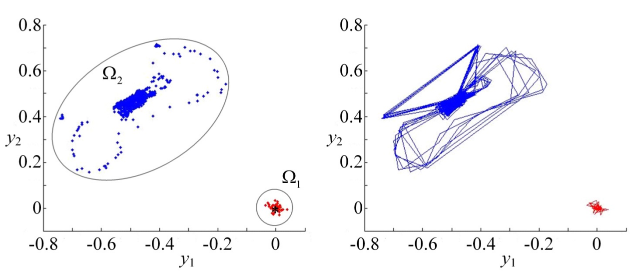
To verify this statement, a series of experiments for the detection of QRS complexes of normal ECG and ECG with different types of PVCs was held. The experiment conditions are as follows:

– the QRS complex of lead I of normal ECG averaged as per 50 periods was selected as a prototype;

– morphological analysis was performed on lead I of ECG with different types of PVCs using a single channel of the designed NF;

– the objects ω^p in AFS were described using the expression (5).

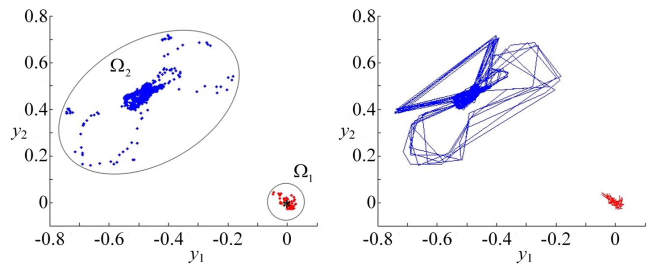
In case of contractions of PVCs left, PVCs right and multifocal PVCs the typical arrangement of objects in the AFS, as well as relevant ECG–hodographs are shown in Figs. 4–10.



a *b*

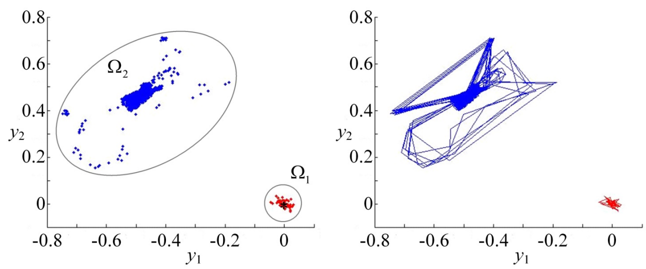
Fig. 4. Visualization of ECG with PVCs left in AFS: *a* – the location of the object relative to ω^p (marked *); *b* – ECG–hodograph

It is easy to notice that on ECG-hodograph complete ECG cycle is visualized as geometric shapes to easily identify an electrocardiogram with atypical cycles that are typical for ventricular arrhythmia.



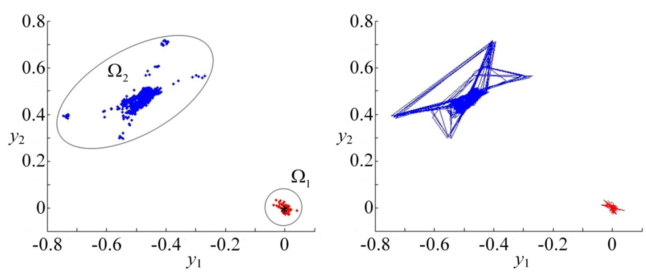
a *b*

Fig. 5. Visualization of ECG with PVCs left, early in AFS АПП: *a* – the location of the object relative to ω^p (marked *); *b* – ECG–hodograph



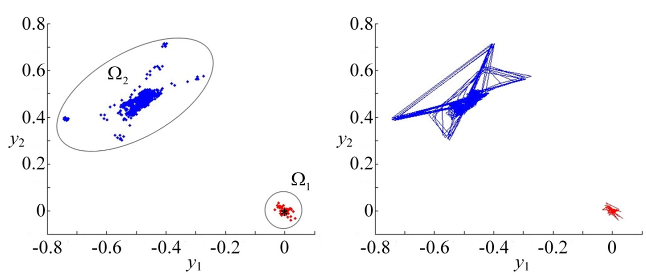
a *b*

Fig. 6. Visualization of ECG with PVCs left, "R on T" in AFS: *a* – the location of the object relative to ω^p (marked *); *b* – ECG-hodograph



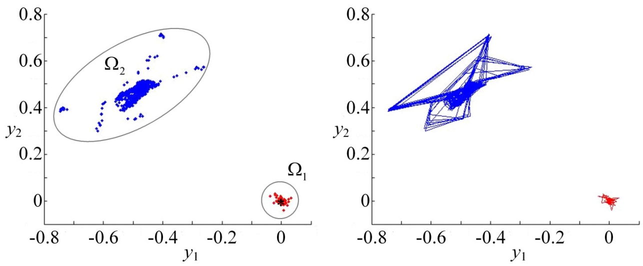
a *b*

Fig. 7. Visualization of ECG with PVCs right in AFS: *a* – the location of the object relative to ω^p (marked *); *b* – ECG-hodograph



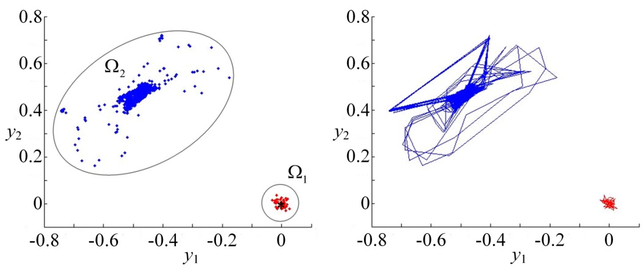
a *b*

Fig. 8. Visualization of ECG with PVCs right, early in AFS: *a* – the location of the object relative to ω^p (marked *); *b* – ECG-hodograph



a *b*

Fig. 9. Visualization of ECG with PVCs right, «R on T» in AFS: *a* — the location of the object relative to ω^p (marked *); *b* — ECG-hodograph



a *b*

Fig. 10. Visualization of ECG with multifocal PVCs in AFS: *a* — the location of the object relative to ω^p (marked *); *b* — ECG-hodograph

8. Discussion of the study results of the alternative feature system diagnostic value

Fig. 3, *a* shows a typical arrangement of objects in the alternative feature space with respect to the prototype ω^p of the QRS complex of lead I of normal ECG. From Fig. 3, *a* it is evident that the objects of classes Ω_1 and Ω_2 represent compact sets, and the objects of the class Ω_2 are divided into three clusters. For normal electrocardiogram, ECG-hodograph is a triangle-type figure (Fig. 3, *b*).

Figs. 3–10 show that the location of the objects of the class Ω_2 differs from the corresponding representation for normal ECG. The objects of the class Ω_2 are not grouped into three separate clusters, wherein for different types of premature ventricular contraction the dots configuration is different (Fig. 4–10 *a*, Fig. 5, *a*, Fig. 6, *a*, Fig. 7, *a*, Fig. 8, *a*, Fig. 9, *a* and Fig. 10, *a*). It should be noted that in addition to the ECG-hodographs triangles, characteristic of a normal ECG, a variety of additional figures are formed. The more so, individual ECG-hodograph points are linked to the time axis, which makes it possible to find those ECG («suspicious» periods), the objects of which differ from the similar objects of normal ECG.

ECG-hodographs with PVCs left (Fig. 4, *b*, Fig. 5, *b*, Fig. 6, *b*), PVCs right (Fig. 7, *b*, Fig. 8, *b*, Fig. 9, *b*) and multifocal PVCs (Fig. 10, *b*) do not only differ from ECG-hodograph of normal ECG, but are also different from each other. Also, there is a significant difference between the location of the objects of the class Ω_2 in AFS for most dangerous extrasystoles «R on T» (Fig. 6, *a* and Fig. 9, *a*) and the corresponding presentation of objects for other types of PVCs (Fig. 4, *a*, Fig. 5, *a*, Fig. 7, *a*, Fig. 8, *a*, Fig. 10, *a*). An even more pronounced pattern is observed in the corresponding ECG-hodographs (Fig. 6, *b* and Fig. 9, *b*).

Thus, the graphical representation of ECG in APP allows visually identify significant differences in the location of the objects of the class Ω_2 for the considered types of PVCs, which makes it possible to carry out their classification.

It is worthwhile to concentrate further investigations on the study of AFS for other types of pathologies, as well as on the development of diagnostically valuable digital characteristics of ECG-hodographs.

9. Conclusions

1. The suggested system of alternative diagnostic features presents the description of BMS with LCF in new feature space with consideration of the useful signal model, which is used in the method developed by the authors of the morphological analysis of BMS with LCF. Due to the presentation of the considered BMS with LCF as ECG-hodograph it becomes possible to identify the ECG with atypical cycles that are typical for PVCs without the need to create training samples.

2. The analysis carried out for determination of the diagnostic value of alternative diagnostic features to detect PVCs showed that there are significant differences between the ECG-hodographs for normal ECG and ECG with the presence of PVCs of various kinds. Due to presentation of additional information in the form of ECG-hodographs, a physician can visually easily and quickly perform a classification of different types of PVCs according to ECG of any duration, which in combination with the classical analysis of «suspicious» ECG periods on the time axis increases the speed and accuracy of the diagnosis.

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