Методы и средства обработки сигналов и изображений

УДК 616.12-089

N.G. Ivanushkina, cand. tech. sci., I.I. Yermakova, d. biol. sci., V.A. Fesechko, cand. tech. sci., K.O. Ivanko, A.A. Popov, cand. tech. sci. I. Khassanov, PhD, B. Hensel, PhD

Pattern Recognition in the Pacemaker Intracardiac Impedance Signal

Предложен метод распознавания образов сигналов внутрисердечного импеданса на основе разложения ковариационной матрицы ансамбля кардиосигналов в базисе его собственных векторов. Амплитуды вычисленных проекций в преобразованном пространстве отражают индивидуальные особенности динамики миокарда и являются оптимальными диагностическими параметрами состояния пациента при формировании обучающих выборок для классификатора.

Рассмотрены алгоритмы обработки кардиосигналов для классификации динамических условий миокарда пациента. Результаты показывают, что определенные таким образом диагностические параметры могут быть использованы для распознавания образов изменяющейся гемодинамики и могут быть реализованы как классификаторы команд для подстройки частоты кардиостимулятора.

A method for pattern recognition of intracardiac impedance signal variation is proposed based on decomposition of the covariance matrix for the cardiac signal ensemble in its eigenvector basis. Magnitudes of the calculated projections in the transformed space reflect individual features of myocardium dynamics and present optimal diagnostic parameters of the patient state while forming learning samples and creating a pattern classifier.

Algorithms of the cardiac signal processing are considered for classification of dynamic conditions of patient's myocardium. The results demonstrate that thus defined diagnostic parameters can be used for pattern recognition of changing hemodynamics and can be implemented as command qualifiers for adjustment of pacing frequency.

Introduction

Access to physiological information is very important for diagnostics of cardiac hemodynamic disorders and for appropriate adjustment of therapy, e.g. cardiac pacing appropriate to the state of the cardiovascular system. For this purpose, diagnostic features in the form of parameters of intracardiac electrograms in time domain [1-4] or decomposition coefficients in different coordinate bases [1-7] can be used.

Complex regulation of the cardiovascular system is based on interrelated multilevel loops including the heart and the peripheral vessels, higher neural centres, different receptors (baroreceptors, chemoreceptors, etc.), afferent and efferent neural paths enabling positive and negative feedback within the whole closed loop system. Normally, to satisfy the increasing hemodynamic needs of the human body under increasing load (physical or emotional) the regulation centres stimulate increases in the heart pumping frequency and in the stroke volume. In pathology, chronotropic incompetence, due to failing sinus node function or/and intracardiac conduction disturbances, can be compensated through electrical therapy with the aid of a pacemaker incorporating a rate-adaptive sensor. Of course, sensors assessing relevant physiological information on hemodynamic needs have highest priority.

The Closed Loop Stimulation (CLS) system uses the so called contractile sensor measuring the intracardiac impedance signal that reflects changes in myocardium contractility. The algorithm principle is based on the well-known physiological mechanism of chronotropic incompetence compensation through increase of heartbeat force. Inotropic compensation of insufficient chronotropic function leads to variation of phase structure of cardiac cycle, in particular, to shortening of its diastolic phase and pre-ejection period (PEP). Phase shift of the intracardiac impedance signal (Fig. 1) is used by the CLS pacemaker as a parameter for evaluation of physiological need in heart rate increase [8]. The parameter is calculated by the pacemaker as the integral surface confined between the impedance signal curves measured at rest (reference) and at load (current curve).

Heartbeat frequency regulation, based on the principle described above, is physiological, as the regulation parameter is linked to regulation of cardiac function by autonomous nervous system (ANS). Thus, replacing the chronotropic function of the sinus node the pacemaker becomes a part of the closed loop system regulating the heart rate. After automatic calibration procedure, during which impedance signal curves in a certain time window of the cardiac cycle (Fig. 1) are evaluated for a certain patient in rest and under physical load, the pacemaker stimulates the heart at frequency, necessary to satisfy hemodynamic needs both at physical and mental stress [9, 10].

Generally, to account for variety of heart function changes, a rather detailed cardiac signal description is needed, generating data arrays of large dimensionality. That leads to complexity of the signal pattern recognition process. Besides the above described algorithm implemented in the CLS pacemaker, the intracardiac impedance signal has been used to recognize the patient state in several other approaches, i.e. based on creation of ensembles of impedance curve parameters [2] and self-learning neural networks [3]. In attempt to minimize the number of diagnostic features of hemodynamic changes, we elucidate here another approach to form optimal learning samples and to classify patterns in transformed subspaces of cardiac signals. The coordinate basis of the new subspaces is composed of the covariance matrix main eigenvectors of the intracardiac impedance signal ensembles obtained with the aid of the CLS-pacemaker.

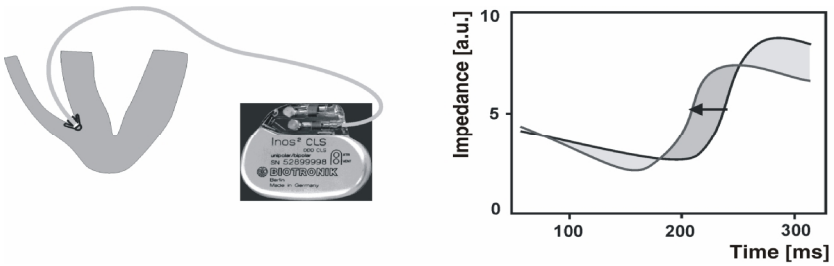

Fig. 1. Variation of the impedance signal under load due to shortening of the diastolic phase of cardiac cycle, namely to shortening of pre-ejection period (PEP)

Materials and methods

To provide pattern recognition of intracardiac impedance signals the following two steps are used (Fig. 2):

- selection of diagnostic features of the patterns;
- creation of pattern classifier.

The corresponding cardiac signals can be discretely sampled *n* times for each heartbeat yielding sequences of *n* values, i.e. *n*-dimensional vectors, used then as basic data. To use that kind of data for discrimination of different myocardium conditions a set different well defined stationary (or quasi-stationary) patients' states must be elaborated.

Selection of diagnostic features of the *n*-dimensional vectors characterizing the impedance signal is a primary task. It can be accomplished in two steps. First, the data will be orthogonally transformed into the basis of eigenvectors. That provides one to one data mapping that preserves the dimensionality of the vectors. Their components now are new coefficients in the transformed domain.

To reproduce specific features of the intracardiac impedance signal the sampling rate should be high enough. On the other hand, the higher the input data dimensionality, more complicated is the pattern classifier. Thus, as a second step, it is crucially important to reduce the dimensionality ($r<n$) still preserving significant signal features (components). A new set of parameters l_1, l_2, … l_r, , i.e. the applied transformation, should result in generation of patterns with maximal distances between the vector groups belonging to different patient states, yet retaining the distances constant inside the groups.

According to the method of eigensubspaces [5-7, 11], any set of cardiosignal realizations, i.e. *n*-dimensional vectors, reflecting a complex process of myocardium excitation and movement, can be associated with its own system of eigenvalues and eigenvectors. The cardiosignal realizations can be expanded in the eigenbasis, i.e. their projections on the eigenvectors can be calculated. These projections (vector components) as well as their integral characteristic, e.g. a total sum of the component squares, can be used for the signal description. The defined characteristic has a very important feature for the qualification process – it possesses maximal contribution of the values of the cardiosignal expansion on eigenvectors of "its own" group.

A classification process of *n*-dimensional realizations of intracardiac impedance signals in the coordinate basis of the eigenvectors [12] begins with composition of a cardiosignal ensemble from several signal realizations measured in a sequence of heartbeats. Each observation (sampling) window should be synchronized with some definite cardiac cycle phase, e.g. with the stimulating pulse. Each cardiosignal realization in the observation window presents an array of *n* discrete values of the signal:

$$\begin{aligned} E_1 &= e_{11}, e_{12}, ..., e_{1n} \\ E_2 &= e_{21}, e_{22}, ..., e_{2n} \\ &\mathbb{M} \\ E_m &= e_{m1}, e_{m2}, ..., e_{mn}, \end{aligned} \qquad (1)$$

where E_1, E_2, … E_m form an ensemble of realizations of the intracardiac impedance signal, e_{mj} ($j = 1, 2, …, n$) are discrete signal values, *m* is the number of the signal realizations (heartbeats), and *n* is the signal sampling factor.

The ensemble of E_i ($i = 1, 2, …, m$) in the form of (1) can be used as a learning sample in order to determine the parameters of affiliation to different groups of the cardiac state K_k ($k = 1, 2, … n$). To learn classification means to determine K_k, derived on E_i, relevant not only for the learning sample E_i, but also for any ensemble *E* of cardiosignals [5, 6, 11]. Figure 3 depicts the algorithm of such signal classification. Analysis of patterns of myocardium dynamics reflected in signals of intracardiac impedance is based on group description in the transformed coordinate basis of eigenvectors defined on sampled signal amplitudes.

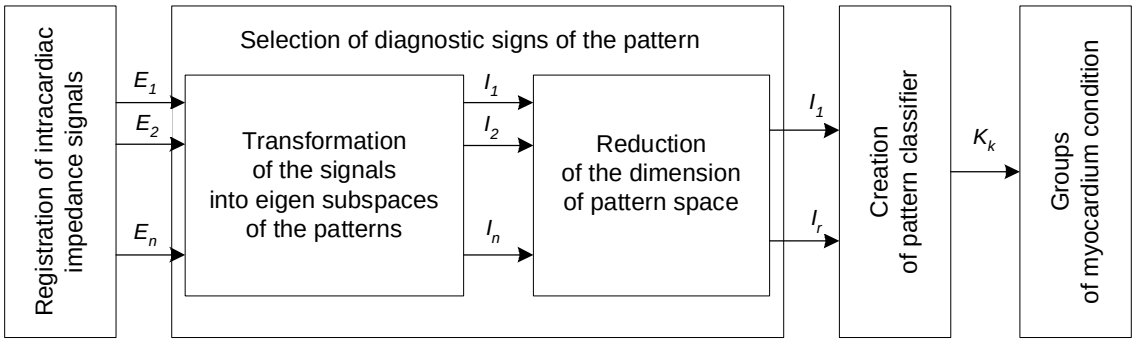

Fig. 2. Flow chart of the pattern recognition process for intracardiac impedance signals

According to the method of eigensubspaces [7, 11], the covariance matrix of the ensemble of cardiosignal realizations, obtained for each group, has the following expansion in the coordinate basis of eigenvectors $V_1, V_2, \ldots V_n$ corresponding to eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_n$:

$$C = \sum_{j=1}^{n} \lambda_j V_j V_j^T . \quad (2)$$

The eigenvectors $V_1, V_2, \ldots V_n$ of the form (2) are orthonormal and ordered according to the appropriate eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$, the main eigenvectors $V_1, V_2, \ldots V_r$ corresponding to the greatest eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_r$.

Each cardiosignal E_i can be presented then as a set of decomposition coefficients – projections on the V_j basis vectors of the eigensubspace of the q–th group:

$$b_{ij}^q = \left\langle E_i \cdot V_j^q \right\rangle . \quad (3)$$

The decomposition coefficients b_{ij}, in the basis of main eigenvectors obtained as a result of inner product of the ensemble of the impedance signal realizations $E_1, E_2, \ldots E_m$ with main coordinates $V_1, V_2, \ldots V_r$ reflect basic information on the patient's heart state. These coefficients can be used in a classification algorithm as new subsets of diagnostic features of lower ($r<n$) dimension.

When $q \neq k$, the signal E_i belongs to a different group, with $\sum (b_{ij})^2$ and λ_j^2 values differing more, the more different are the groups k and q, and, consequently, the more different are their eigensubspaces. Then, projection of the signal E_i onto the V_j^q eigenvector of the "strange" group q is equal to:

$$b_i^q = \sum_{j=1}^{n} b_{ij}^k \left\langle V_j^k V_j^q \right\rangle . \quad (4)$$

While creating the classifier, it is recommended to use the quantitative characteristic of E_i cardiosignal decomposition on main vectors of the eigensubspace of the group k, i.e. H_k, which represents a square of the signal E_i projection:

$$H_k = \sum_{j=1}^{r_k} \left\langle E_i, V_j^k \right\rangle^2 = \sum_{j=1}^{r_k} (b_j^k)^2 . \quad (5)$$

Where r_k is dimension of the eigensubspace, built on the main eigenvectors of the group k.

In view of the fact, that the introduced characteristic is maximal for the cardiosignal E_i expansion on the main vectors of the eigensubspace of its group, the classification criterion can be formulated as follows:

"if $h_{kq} = H_k - H_q > 0$, $q = 1, 2 \ldots, \nu \quad (q \neq k)$,

$$\text{then } K = k\text{"} \quad (6)$$

One of the ways to achieve the maximal distance between the groups is to select the dimension of the transformed subspace of the patterns' features. In order to maximize the difference between expansion characteristics of intracardiac impedance signals on the vectors of their own group and the vectors of the different groups, it is necessary to select the dimension of the subspace of main eigenvectors of each group $r_k = r_1, \ldots, r_n$ in the proposed algorithm (Fig. 3), so that the maximum of the form (6) would be provided.

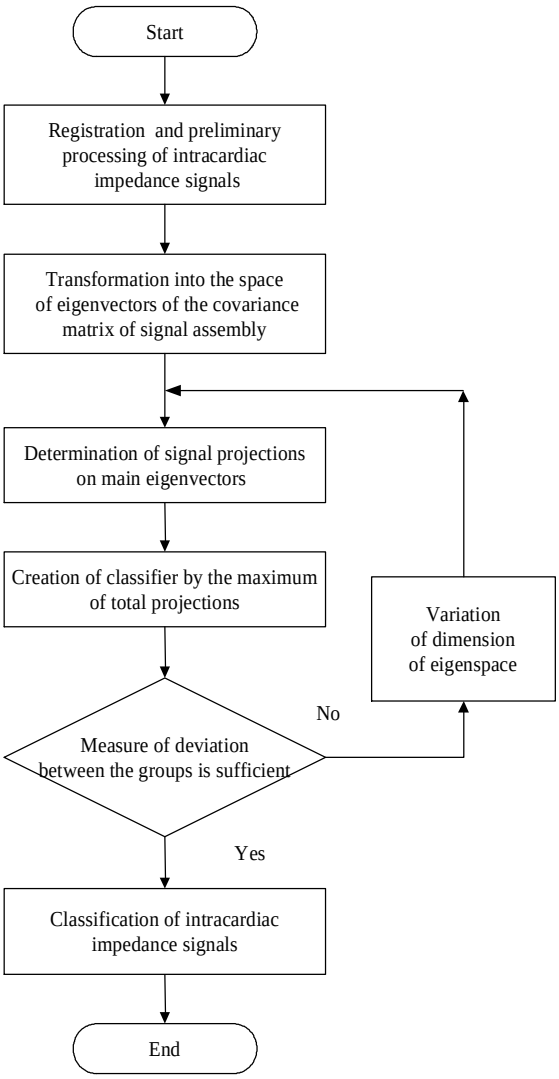

Fig. 3. The classification algorithm for intracardiac impedance signalsWith $q = k$, the signal E_i is projected onto the subspace vectors of the same group, to which it belongs. Therefore the projections, calculated according to (3), would allow the most precise representation of the E_i by a linear combination of eigenvectors. Besides that, the square of E_i signal projection on V_j vector is larger, the larger is the corresponding eigenvalue λ_j, according to the properties of decomposition in the basis of eigenvectors.

Thus, according to determined r_k values of the analyzed proper subspaces, the ordered feature set of intracardiac impedance signals of lower dimension could be used.

Results

The described discrimination algorithm has been tested on sets of intracardiac impedance signals obtained for 70 patients with the CLS pacemaker implanted for rate adaptive heart pacing. The impedance signal has

been measured on the electrode located in the right ventricle apex against the pacemaker housing (Fig. 1) [1]. The signal has been sampled at frequency of 128 Hz in a time window of 47÷289 ms after ventricular excitation, giving thus a set of 32 amplitude values for each heartbeat.

Intracardiac impedance signals have been measured for each patient in four stationary states with different levels of physical activity, corresponding to four different conditions of myocardium dynamics:

- group I – "physical exercise, standing or sitting" – exercise ("exr");
- group II – "frequent (overdrive) stimulation in rest, sitting" – overdrive ("ovr");
- group III – "rest, sitting" – rest ("rst");
- group IV – "rest, supine" – supine ("sup").

Characteristic impedance signals measured in one of the patients in the four different myocardium states are presented in Figure 4. Learning samples of normalized realizations of intracardiac impedance signals were created for each condition state (group), the size of learning samples varying from 10 to 30 realizations. An example of a learning sample of 30 realizations, corresponding to the group 3 – hemodynamic state in the sitting position without physical exercise, is shown for one of the patients in Figure 5.

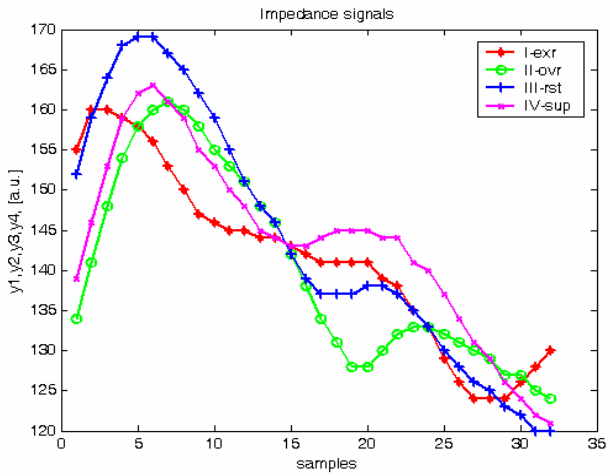

Fig. 4. Characteristic signals of intracardiac impedance measured in one of the patients in four different states: exr – exercise, ovr – overdrive, rst – rest (sitting), sup – supine (rest)

The signals not applied for the learning procedure were used for the discrimination algorithm verification. In numerical experiments on pattern recognition of intracardiac impedance signals, covariance matrices of ensembles were composed of selected realizations; proper subspaces and total projections on three main eigenvectors in "native" and "strange" subspaces were defined. Test-sequences of each group were delivered to the classifier in turns.

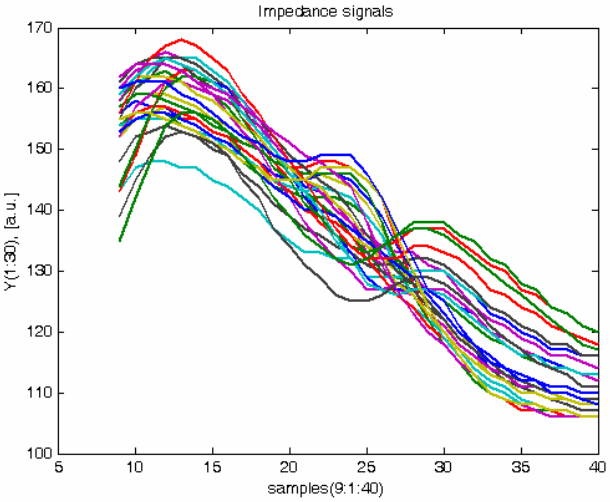

Fig. 5. An example of a learning sample: 30 measured signals of intracardiac impedance measured in one of the patients in the sitting position without physical load (rest state)

Table 1 presents the values of the state features – total projections of 31-th test realization of the signal ensemble for each group after the expansion in eigensubspaces of the groups 1, 2, 3 and 4.

The results of 31st intracardiac impedance test signal's classification for groups 1-4, shown in Table 1, demonstrate the maximal values of the signs, characteristic for recognition of the "own" group.

Conclusion

The numerical experiments on pattern recognition of intracardiac impedance signals in 70 patients have confirmed theoretical considerations of the method of eigensubspaces. All the signals of learning sample were correctly referred to their groups with the integral criterion features – maximal values of total projections in the basis of three main eigenvectors. For the test signals, not included into the learning sample, the indices of classification sensitivity varied in the range of 78÷97%.

Still, the data presented in Table 1 in some cases show very small differences between the values of total projections on the "native" and on the "strange" groups, e.g. the test signal of group III in eigensubspaces of groups III and IV). This phenomenon occurs in cases of relatively close location of eigensubspace domains for different groups in certain patients and could reflect the existence of peculiarities in their heart function. It should be noted that the conditions of groups III and IV, both corresponding to the physiological condition of rest (in

Table 1. Total projections of test signals of groups I-IV in "native" and "strange" subspaces

Test sequences		Group I	Group II	Group III	Group IV
realization 3I	Group I	**0.9997**	0.8976	0.7563	0.8567
realization 3I	Group II	0.9727	**0.9879**	0.9017	0.8251
realization 3I	Group III	0.9535	0.9773	**0.9883**	0.98901
realization 3I	Group IV	0.8812	0.9672	0.9764	**0.9986**

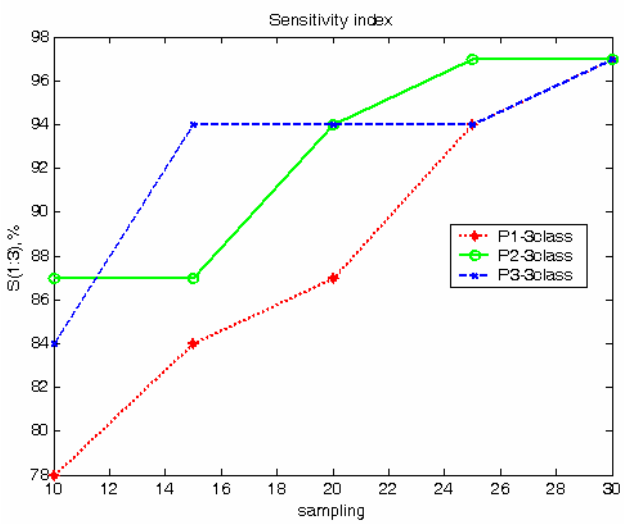

Fig. 6. Sensitivity index of classification of intracardiac impedance test signals, depending on the size of learning sample, in 3 patients (P1, P2, P3)

sitting and supine positions, respectively) are the most similar, though, in absence of pathology, are characterized by different contractile function of myocardium and its dynamics. The investigations were carried out in patients, suffering from cardiac rhythm abnormalities and often having decreased dynamic reserves of myocardium, which leads to still higher approximation of different, but similar enough groups of myocardium dynamics condition.

Generally, in order to increase the degree of divergence between the groups, it is necessary, besides the selection of proper subspace dimension, to pay attention to the creation of learning sample. The influence of its size on the authenticity of the obtained results is shown in Figure 6. Its necessity is also conditioned by the fact that, as mentioned before, the contractile CLS sensor responds to both physical and mental stress, and the level of the latter one can hardly be controlled in the experiment.

Furthermore, additional procedures for transformation of different states eigensubspaces can be applied that could increase their discrimination accuracy.

Thus, it has been demonstrated that the method of eigensubspaces enables discrimination of patterns of intracardiac impedance signals, based on strongly reduced number of parameters – total projections in the basis of major eigenvectors of covariance matrix of signal ensembles. Differential criteria of intracardiac signal features in the bases of “native” and “strange” signal groups can be used for determination of the signal vector eigensubspace dimension. Diagnostic features – here, total projections of intracardiac impedance signal vectors – can be used in rate adaptive pacemaker algorithms.

References

1. *M. Schaldach*, H. Hutten. Intracardiac impedance to determine sympathetic activity in rate responsive pacing. PACE, 15, 1778-1786, 1992.
2. *S. Berdyshev*, V. Berdyshev, O. Anosov, I. Khassanov, M. Schaldach. Topical Mathematical Problems in Electrotherapy of the Heart. Progress in Biomedical Research. 4 (5), 553-557, 1999.
3. *S.V. Berdyshev*, V.I. Berdyshev, I. Sh. Khassanov, M. Schaldach. Self-learning neural networks for the definition of patient’s condition based on the ANS-pacemaker impedance signal. Progress in Biomedical Research, Supplement A. 6(1), 79-82, 2001 (in Russian).
4. *I. Sh. Khassanov*, W. Mayer, B. Hensel. Pacemaker intracardiac impedance signal for hemodynamics optimization. Arrhythmology Bulletin. (Supplement A), 35, 79, 2004 (in Russian).
5. *N. Ahmed*, K.R. Rao. Orthogonal transformations in processing of numeral signals. Ed. N.B. Fomenko. Moscow, “Svyaz” 1980, 248 p.
6. *V.G. Abakumov*, O.I. Rybin, Y. Svatosh. Biomedical signals. Genesis, processing, monitoring. Kiev, Nora-Print, 2001, 453 p.
7. *V.V. Shakin*. Selection of the classification criteria in the method of proper subspaces. Modeling and automatic analysis of electrocardiograms. Moscow, “Nauka”, 103-114, 1973 (in Russian).
8. *M. Schaldach*. PEP-gesteuerter Herzschrittmacher. Biomed. Technik. 34 (7/8), 177-184, 1989.
9. *S.V. Berdnikov*, O.V. Beliaev, I.Sh. Khassanov, M. Schaldach. Frequency adaptation, based on sensors of myocardium contractility and motion energy: comparative analysis. Materials of the III International Congress on Electrostimulation and Clinical Cardiac Electrophysiology, St. Petersburg, 5-7 February, 1998: 64 (in Russian).
10. *S.V. Berdnikov*, O.V. Beliaev, I. Khassanov, M. Schaldach. Contractility Sensor and Motion Sensor Based Rate Adaptive Pacemakers: Comparative Clinical Study. Archives des Maladies du Cœur et des Vaisseaux 91 (N Special III). Proceedings of the 11th International Congress “Cardiostim 98”, Nice, 17-20 June 1998: 306.
11. *J. Tou*, R. Gonzales. Pattern recognition principles. Moscow, “Mir”, 1978, 407 p. (in Russian).
12. *N.G. Ivanushkina*. Method of electrocardiogram processing in the optimal coordinate basis. Electronics and Communication, 12,114-115, 2001.