Original research

Correction of the recording artifacts and detection of the functional deviations in ECG by means of syndrome decoding with an automatic burst error correction of the cyclic codes using periodograms for determination of the code component spectral range

Part 1: Basic principles of the novel approach

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Aims	This paper describes a novel approach to the analysis of electrocardiographic data based on the consideration of the repetitive P, Q, R, S, T sequences as cyclic codes. In Part I we introduce a principle similar to the syndrome decoding using the control numbers, which allows correcting the noise combinations.
Materials and methods	We propose to apply the burst-error-correcting algorithms for automatic detection of the ECG artifacts and the functional abnormalities, including those compared to the reference model. Our approach is compared to the symbolic dynamics methods. During the automated search of the code components (i.e. point values and spectral ranges one-to-one corresponding to P, Q, R, S, T) considered in Part II, the authors apply the Lomb-Scargle periodogram method with the phase control which allows to determine the code components not only from the main harmonics, but also using the sidebands, avoiding the phase errors.
Results	The results of the method testing on rats with the heart failure using a simplified telemetric recording from the implantable chips are given in Part III. A complete independence of the results of the determination of the code points (fingerprints) from the variables for which the calculation is performed is shown. We also prove the

robustness of the above approach with respect to the most types of the non-adaptive filtration.

Conclusion	The above method can be useful not only for experimental medicine, but also for veterinary and clinical diagnostic practice. This method is adequately reproduced both on animals and human ECG, except for some constant values.
Keywords	ECG • Cyclic codes • Error corrections • Syndrome decoding • Control numbers • Lomb-Scargle periodogram methods • Fingerprinting
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Is it rational to use the cyclic codes in ECG interpretation?

It is well known that a normal sinus rhythm is characterized by the periodicity and regularity of the P, Q, R, S, T components, while any deviations from the cycle (beat-to-beat interval) belong to HRV (Heart Rate Variability) and are usually considered as the cycle length variability, RR variability, heart period variability, etc. Thus, any method based on the detection of the cyclicity, iteration interval or the period of the signal (including a single component shifted one) can be successfully applied for the periodicity analysis and diagnostics of the functional abnormalities (especially for arrhythmias) using ECG, as well as for the detection and correction of the artifacts of the electrocardiographic data computer identification associated with the improper fixation of the electrodes on the patient's body leading to the changes in the waveform or periodicity of the cardiac cycle components. In particular, this recognition process with the parallel correction is very useful both for telemetric electrocardigraphic analysis in experimental veterinary medicine and for Holter monitoring on the active patient, since the dynamics of the monitored organism inevitably affects the ECG waveform and periodicity [1,2].

The automatic decomposition of the ECG signal into the principal P, Q, R, S, T components makes it possible to establish one-to-one correspondence between them and the computer font symbols which allow to perform fingerprinting of the functional states and organic disorders changing the heart rhythm. A similar approach can be implemented within symbolic dynamics where the electrophysiological activity of the heart is considered as a dynamic system with the points of the phase space represented by the sequential set (a so-called alphabet, e.g. P-Q-R-S-T), and the certain disruptions in the heart rhythm can be considered as the sequential shift [3]. In this context we deliberately define the PQRST-alphabet in terms of the digital sequential logic, since it considers the operation background of the systems modeled in a discrete form, which is important for diagnostics and researches with the check experiments. From the mathematical standpoint it would be more accurate to define it using the Bernoulli automorphism, invariant closed subsets and invariant measures, but it is almost useless for the purposes of this methodical paper, while the application of the classical analytical tools – the asymptotic methods and the perturbation theory series, does not satisfy this task from the metrological positions.

The first application of symbolic logic to the cardiographic data analysis dates back to the late 1970s – early 1980s [4,5] and becomes methodologically complete during the period from 1982 to 1986 which resulted in the development of the symbolic logic notation (language and "alphabet") describing the sinoatrial node activity and its rhythm as a regulator of the contractile frequency [6], symbolic systems of analysis and visualization for electrical mapping of the heart with the predicate elements being the symbols of the spatiotemporal mapping [7] and for automatic interpretation of the myocardial scintigrams [8] based on the mathematical logic predicates of the Horn clause in the logic programming language PROLOG.

This laid a physico-technical basis for the spatio-temporal, and hence, morphophysiological interpretation of the cardiological data within symbolic logic and at the same time resulted in the publication of several papers combining morphological measurements with the computer-assisted symbolic logic analysis (e.g., see a well known paper on the myocardial vascular microangiopathy [9]). However, being directly related to the progress and spread of the computer technology, a full introduction of symbolic diagnostics to the routine medical practice became possible only in the 1990-th, particularly due to the required transition from symbolic logic to symbolic dynamics necessary for identification of the transient cardiac syndromes associated with the nonlinear phenomena determined from the ECG.

The very first complex application of symbolic dynamics in cardiology for the above purpose dates back to the middle 1990-th [10], while nonlinear, chaotic and noise phenomena in HRV have been quantitatively studied earlier [11]. To date the application of symbolic dynamics in HRV analysis has already become a routine procedure [12]. A significant advantage of symbolic dynamics is the simplicity of its mathematical algorithms involved in detection of the correlations between the cardiac and respiratory syndromes and factors [13], as well as in the determination of the cardio-neurological correlations and cause-and-effect relationships (in the framework of the predicate logic) including significantly nonlinear HRV measurements [14,15]. To date it does not make any difficulties, since the parameters causing nonlinearity of the HRV curves are well studied [16] and the regimes corresponding to the transient phenomena and rhythmic (amplitude-frequency) distorsions can be easily expressed in terms of symbolic dynamics [17]. It is also essential that application of symbolic dynamics allows to detect and analyze the natural modulations of the cardiac activity independently of their source and origin [18,19]. One of the most clinically relevant applications of the above approach is a long-term monitoring of the cardiac rhythm change in the age physiology and pathology [20,21], starting from the fetal stage of development [22,23].

The possibility of the multi-scale analysis of the cardiac activity and HRV using symbolic dynamic techniques [24,25] provides broad prospects for diagnostics. Thus, the application of symbolic dynamics to the classification of electrocardiographic signals [26] allows to diagnose various diseases, including those difficult to be identified at the early stages due to the lack of a clear clinical picture, such as dilated cardiomyopathy [27]. As for the mathematical foundations of the above classification, one should consider different existing approaches to HRV analysis in symbolic dynamics [28]. This diversity results from the difference of variables, boundary conditions and confidence intervals of the accurate parameter detection and quantization determining the so-called "pathological" values. Of special interest is the correlation adjustment of the data typical for cardiorespiratory comparative (i.e. comparison of the syndromes) and correlation studies. For example, the known relationship between the cardiac and respiratory cycles expressed in terms of symbolic dynamics [29] provides an automatic detection (without any external models [30]) of the deviations from the above function indicating the presence of either functional disorders or organic pathologies. This method (with the known cardiorespiratory interactions expressed in the symbolic dynamics notation [31]) allows to detect a number of diseases, such as hypoxia / ischemia effects [32], obstructive sleep apnea [33], interactions between the cardiac and respiratory oscillators associated with the stages of sleep in healthy children [34], etc. It is noteworthy that in such cases a similar respiration pattern variability analysis is also performed and the corresponding optimized symbolic dynamics approaches for the pattern analysis and calibration are also developed [35,36].

All the above methods are based on the monitoring of the deviations from the beat-to-beat interval and HRV – cycle length variability, RR interval variability and heart period variability, e.g. symbolic dynamic analysis of beat-to-beat interactions of heart rate and systolic blood pressure [37], assessment of the RR versus QT relation by the symbolic dynamics method [38], and the classical concepts about the heart rhythm are quite sufficient for analysis at this level [39]. Another positive aspect of the electrocardiographic PQRST-sequence analysis using symbolic dynamics methods is the possibility of the casuality analysis within the cycle and in its relevant repeats [40] despite the fact that in the framework of symbolic dynamics hidden Markov models are also developed without any dependence of the current parameter value from the previous state of the system [41], which seem to be regarded as the Bayesian belief networks. In this regard one can conclude that symbolic dynamics in cardiology operates both at the state-space of a periodic PQRST-oscillator / pacemaker [42] with a high determinism inherent to the healthy heart [43] and at a noisy case [44] with an indeterminism caused by a number of states with a various degree of proximity of the real PQRST to the model one according to the Hamming theory [45]. However, it is important to find out which symbolic dynamics can operate in presence of the intermediate or "parasitic" (considered as artifacts) states?

Many authors and users try to minimize the bit depth of the data under processing reducing the point phase space of symbolic dynamics to the binary trigger simulation: methods for analysis of the binary sequences are adapted to the cardiac activity analysis [46], the information entropy of such sequences is also calculated and fitted [47] and the special systems based on the above binary approach for HRV pattern biomedical classification at the autonomic modulation are also developed [48]. However, this approach reduces both the diagnostic accuracy at the registration stage and the robustness of the signal processing.

At the same time for dynamical systems which can be attributed to symbolic dynamics mapping is defined as a sequence shift by a single symbol which is described by either Markov or Bernoulli shift conditions, so the shift in a reduced phase space (with a reduced symbol alphabet) decreases the quality of the mapping compared to those of the standard full alphabet (P, Q, R, S, T). Thus, we do not claim that the above cited works are not correct, but we postulate the need for an alternative method / approach which, on the one hand, will take into account the cyclic nature, regularity and periodicity of the ECG, and, at the other hand, will be able to detect the arrhythmia and the recording artifacts (i.e. the delay and "outrunning" in a readback mode).

A biomathematical approach proposed

We propose to solve the above problems by using a mathematical apparatus of the cyclic codes' decoding [49]. A regular iteration of the PQRST-sequence (P–wave, QRS–complex, T–wave) in the Einthoven's triangle suggests that the above cyclic dynamics can be described by cyclic codes. In general, a cyclic code at the ECG is a linear block (n,k) – code which being shifted by a single step to the left produces a code word which belongs to the same code, and the manifold of the code words is a set of polynomials degree $n-1$ and less, dividing by the generator polynomial $g(x)$ degree $r=n-k$, which is a factor of the binomial x^n+1, and the code words in this code are represented as polynomials: $v(x)=v_{n-1}x^{n-1}+v_{n-2}x^{n-2}+\ldots+v_1x^1+v_0x^o$, where n – is the code length; v_i – coefficients from the field $GF(q)$. If we interpret the heart rhythm as a stable code (due to the automatism of the heart muscle and autonomous regulation) with the errors indicating physiological abnormalities, one can represent a PQRST sequence as a "code over a field $GF(PQRST)$" analogous to the binary code being a code over a field $GF(2)$. From the technical positions, the code shift either to the left or to the right will determine the cyclic window, but this will not be included in a statistical analysis. This is consistent with the symbolic dynamics theory in a shift context [50].

An error detection with respect to the reference code range with the normal rhythm, pulse interval, force and tension, and the absence of the rhythm failures can be achieved using an error polynomial $e(x)$ and a syndrome polynomial $S(x)$. An error polynomial can be determined from the equation: $e(x)=v^\bullet(x)+v(x)$, where $v^\bullet(x)$ and $v(x)$ are polynomials representing an accepted (with an error) and transmitted code words, respectively, with non-zero coefficient positions in $e(x)$ corresponding to the errors. An essential feature of some cyclic codes is the ability to correct burst errors. In the case of the cardiac activity this function is performed due to the bioelectric heart automatism and compensatory homeostatic effects.

A syndrome polynomial used in cyclic code decoding is given by a remainder of the division of the code word by the generator polynomial: $S_j(x)=R_{g(x)}\left|v^\bullet(x)\right|$ or $S_j(x)=R_{g(x)}\left[v^\bullet(x)+e_j(x)\right]=R_{\ g(x)}\left[e_j(x)\right]$, i.e. directly depends on the error polynomial $e(x)$, and hence, can be applied to the generation of a syndrome table which is used in the decoding process and contains a list of the error polynomials as well as the list of syndromes determined from the expression $S_j(x)=R_{g(x)}\left[e_j(x)\right]$. Automatic correction of the recording artifacts can be performed by means of a table search of the polynomial $e(x)$, which after summation with the code word gives a new corrected code word: $v_j(x)=v_j^\bullet(x)+e_j(x)$

From the standpoint of the algebraic block code theory, the code cyclicity imposes serious restrictions on the code word set, which simplifies the decoding procedure in electrocardiography, since both Bose-Chaudhuri-Hocquenghem (BCH) codes capable of correcting several independent errors and Golay codes which correct single, double and triple errors are sufficient enough in this case, as nothing more is required. The length of a primitive cyclic code, when $n=q^m-1$ over $GF(PQRST)$ may be quite sufficient for interference-free data interpretation. The proximity of interpretation and pointedness of the mathematical apparatus (formalism) allows to use the cyclic code decoding methods in the same manner as the symbolic dynamics methods with the ECG sequences recognition as algebraic curves [51]. This is facilitated by the presence of several systolic architectures for cyclic code decoding [52] which allows to perform the coding even in the extremely simplified case – within the classical binary sequences' analysis discussed above [46].

Moreover, there is a number of quasi-cyclic codes [53,54] which include in the framework of this approach the ECG codes over the field $GF(PQRST)$. This is promoted by the existence of the quaternary quasi-cyclic codes [55]: if we consider one of the wave components as a "punctuation mark" in the structural numeration of the ECG components [56] (which corresponds to the consideration of the heart automatism as the analog "sequential machine" [57] but is not applicable to any other non-systematic irregular electrophysiological sequences [58]), so codes over the field $GF(PQRST)$ will appear to be ternary ones with a fixed point. This requires an automatic determination of the heart rate as a cyclic code rate [59] and beating [60] with automatic positioning (fingerprinting) of the "punctuation point". For this purpose computer analysis of cyclic codes applies the weight spectra [61] which may be successfully used in cardiography where symbolic dynamics analysis is often combined with the spectral analysis [62], especially for the search of distortions [63].

The feasibility of introduction of the above approach to the clinical practice at the current stage can be proved by the already accomplished (within the US and the EU) implementation of the combined spectral frequency, pulse-time and symbolic dynamic methods of the heart rhythm variability in hepatology [64], gender fingerprinting using combined spectral and symbolic dynamic techniques both in the prevention and clinical examination [65], combination of the morphometric, ultrastructural, optical microscopic and symbolic-logical analysis in cardioendocrinology at myocardial microangiopathy and experimental diabetes [66]. In the areas where spectral analysis is traditionally used, such as the analysis and detection of ventricular tachycardia [67], symbolic dynamics approaches are implemented to perform the same functions [68]. One of the current trends is combined multiparameter analysis using wavelet-based symbolic representations [69] which does not allow to make a clear distinction between the spectral and symbolic approaches. In this regard, we propose a novel approach where the elements of symbolic dynamics are determined by the computer rather than by a physician / operator, automatically performing "fingerprinting" of the ECG signal with the subsequent comparison to the statistically relevant recognizable spectral components (and the related harmonics) in the indicator dynamics (e.g. in the form of cumulative spectral decay), indicating their belonging to the certain components of the cyclic code over a field $GF(PQRST)$. The statistical deviation values [70] in this case will indicate the heart rate variability in symbolic dynamics [71], and the presence of nonlinear phenomena after detection and detrending of the fluctuations will indicate certain biophysical mechanisms rather than the recording artifacts [72]. From the standpoint of the cyclic code mathematics substituting symbolic dynamics, detection of the ectopic pulses in nonlinear dynamics of the heart rhythm [73], will be an essential part of the code error detection procedure [74].

Thus, the main aim of this paper was to demonstrate the possibilities and the prospects of the concept proposed (i.e. spectrally-mediated determination and fluctuating code range specification during ECG interpretation). For this purpose it is also necessary to demonstrate the stability of the frequency components' determination (fingerprinting) and the independence of their values from the discrimination and filtration types, as well as from the variables used. These problems will be considered in the next part of this work.

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Statement on ethical issues

Research involving people and/or animals is in full compliance with current national and international ethical standards.

Conflict of interest

None declared.

Author contributions

All authors prepared the manuscript and analyzed the data, E.D.A. drafted the manuscript. All authors read the ICMJE criteria for authorship and approved the final manuscript.

References

1. Coumel P, Leclercq JF, Attuel P. Computerized Arrhythmia Analysis of the Holter Recordings. Develop. Cardiovasc. Med. 1984;37:82-92.

2. Bartolo A, Dzwonczyk RR, Roberts O, Goldman E. Description and validation of a technique for the removal of ECG contamination from diaphragmatic EMG signal. Med. & Biol. Eng. & Comput. 1996;34(1):76-81.

3. Vasyukevich V. Asynchronous Operators of Sequential Logic: Venjunction & Sequention. Berlin – Heidelberg: Springer; 2011. 126 p.

4. Moore GW, Hutchins GM, Bulkley BH. Certainty levels in the nullity method of symbolic logic: application to the pathogenesis of congenital heart malformations. Journ. Theor. Biol. 1979;76(1):53-81.

5. Moore GW, Hutchins GM. Symbolic logic analysis of congenital heart disease. Path. Res. Pract. 1981;171(1):59-85.

6. Brownlee RR, Shimmel-Golden JB, Del Marco CJ, Furman S. A new symbolic language for diagramming pacemaker / heart interaction. Pac. Clin. Electrophys. 1982;5(5):700-9.

7. Slavkovský P, Hulín I. Zobrazenie elektrického poľa serdca pomocou znakových máp. Bratis. Lek. Lis. 1985;83(5):530-42.

8. Rosenberg S, Itti R, Benjelloun L. Symbolic reasoning about myocardial scintigrams in PROLOG. Eur. Journ. Nucl. Med. 1986;12(2):65-8.

9. Tasca C, Stefaneanu L, Vasilescu C. The myocardial microangiopathy in human and experimental diabetes mellitus. (A microscopic, ultrastructural, morphometric and computer-assisted symbolic-logic analysis). Endocrinologie, Apr-Jun 1986;24(2):59-69.

10. Wessel N, Schirdewan A, Malik M, Voss A. Symbolische Dynamik – eine eigenständige Methode zur Erkennung von nichtlinearen Phänomenen der Herzschlagregulation. Biomedizin. Tech. 1998;43:510-1.

11. Kurths J, Voss A, Saparin P, Witt A, Kleiner HJ, Wessel N. Quantitative analysis of heart rate variability. Chaos. 1995;5(1):88-94.

12. Cesarelli M, Romano M, Bifulco P, Improta G, D'Addio G. An application of symbolic dynamics for FHRV assessment. Stud. Health Technol. Inform. 2012;180:123-7.

13. Baumert M, Javorka M, Kabir MM. Joint symbolic analyses of heart rate, blood pressure, respiratory dynamics. Journ. Electrocard. 2013;46(6):569-73.

14. Yeragani VK, Nadella R, Hinze B, Yeragani S, Jampala VC. Nonlinear measures of heart period variability: decreased measures of symbolic dynamics in patients with panic disorder. Dep. Anx. 2000;12(2):67-77.

15. Kim JS, Park JE, Seo JD, Lee WR, Kim HS, Noh JI, Kim NS, Yum MK. Decreased entropy of symbolic heart rate dynamics during daily activity as a predictor of positive head-up tilt test in patients with alleged neurocardiogenic syncope. Phys. Med. Biol. 2000;45(11):3403-12.

16. Maestri R, Pinna GD, Accardo A, Allegrini P, Balocchi R, D'Addio G, Ferrario M, Menicucci D, Porta A, Sassi R, Signorini MG, La Rovere MT, Cerutti S. Nonlinear indices of heart rate variability in chronic heart failure patients: redundancy and comparative clinical value. Journ. Cardiovasc. Electrophysiol. 2007;18(4):425-33.

17. Magagnin V, Bassani T, Bari V, Turiel M, Maestri R, Pinna GD, Porta A. Non-stationarities significantly distort short-term spectral, symbolic and entropy heart rate variability indices. Physiol. Measur. 2011;32(11):1775-86.

18. Guzzetti S, Borroni E, Garbelli PE, Ceriani E, Della BP, Montano N, Cogliati C, Somers VK, Maliani A, Porta A. Symbolic dynamics of heart rate variability: a probe to investigate cardiac autonomic modulation. Circulation. 2005;112(4):465-70.

19. Tobaldini E, Porta A, Wei SG, Zhang ZH, Francis J, Casali KR, Weiss RM, Felder RB, Montano N. Symbolic analysis detects alterations of cardiac autonomic modulation in congestive heart failure rats. Aut. Neurosci. 2009;150(1-2):21-6.

20. Takahashi AC, Porta A, Melo RC, Quitério RJ, da Silva E, Borghi-Silva A, Tobaldini E, Montano N, Catai AM. Aging reduces complexity of heart rate variability assessed by conditional entropy and symbolic analysis. Intern. Emerg. Med. 2012;7(3):229-35.

21. Cysarz D, Linhard M, Edelhäuser F, Längler A, Van Leeuwen P, Henze G, Seifert G. Symbolic patterns of heart rate dynamics reflect cardiac autonomic changes during childhood and adolescence. Aut. Neurosci. 2013;178(1-2):37-43.

22. Van Leeuwen P, Cysarz D, Lange S, Geue D, Groenemeyer D. Quantification of fetal heart rate regularity using symbolic dynamics. Chaos. 2007;17(1):1-9.

23. Van Leeuwen P, Cysarz D, Lange S, Grönemeyer D. Increase in regularity of fetal heart rate variability with age. Biomedizin. Tech. 2006;51(4):244-7.

24. Valencia JF, Vallverdú M, Cygankiewicz I, Voss A, Vazquez R, Luna AB, Caminal P. Multiscale regularity analysis of the Heart Rate Variability: stratification of cardiac death risk. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2007; pp. 5947-50.

25. Cysarz D, Edelhäuser F, Van Leeuwen P. Multiscale analysis of acceleration and deceleration of the instantaneous heart rate using symbolic dynamics. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2011; pp. 1965-8.

26. Parlitz U, Berg S, Luther S, Schirdewan A, Kurths J, Wessel N. Classifying cardiac biosignals using ordinal pattern statistics and symbolic dynamics. Comp. Biol. Med. 2012;42(3):319-27.

27. Baumert M, Baier V, Truebner S, Schirdewan A, Voss A. Short- and long-term joint symbolic dynamics of heart rate and blood pressure in dilated cardiomyopathy. IEEE Trans. Biomed. Eng. 2005;52(12):2112-5.

28. Cysarz D, Porta A, Montano N, Van Leeuwen P, Kurths J, Wessel N. Different approaches of symbolic dynamics to quantify heart rate complexity. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2013; pp. 5041-4.

29. Caminal P, Giraldo BF, Vallverdú M, Benito S, Schroeder R, Voss A. Symbolic dynamic analysis of relations between cardiac and breathing cycles in patients on weaning trials. Ann. Biomed. Eng. 2010;38(8):2542-52.

30. Baumert M, Brown R, Duma S, Broe GA, Kabir MM, Macefield VG. Joint symbolic dynamics as a model-free approach to study interdependence in cardio-respiratory time series. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2012; pp. 3680-3.

31. Kabir MM, Saint DA, Nalivaiko E, Abbott D, Voss A, Baumert M. Quantification of cardiorespiratory interactions based on joint symbolic dynamics. Ann. Biomed. Eng. 2011;39(10):2604-14.

32. Reulecke S, Schulz S, Bauer R, Witte H, Voss A. Quantification of cardiovascular and cardiorespiratory coupling during hypoxia with Joint Symbolic Dynamics. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2011; pp. 2695-8.

33. Ravelo-García AG, Saavedra-Santana P, Juliá-Serdá G, Navarro-Mesa JL, Navarro-Esteva J, Álvarez-López X, Gapelyuk A, Penzel T, Wessel N. Symbolic dynamics marker of heart rate variability combined with clinical variables enhance obstructive sleep apnea screening. Chaos. 2014;24(2):024404-1–024404-8.

34. Kabir MM, Kohler M, Abbott D, Baumert M. Quantification of cardio-respiratory interactions in healthy children during night-time sleep using joint symbolic dynamics. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2011; pp. 1459-62.

35. Caminal P, Mateu J, Vallverdú M, Giraldo B, Benito S, Voss A. Estimating respiratory pattern variability by symbolic dynamics. Meth. Inf. Med. 2004;43(1):22-5.

36. Caminal P, Vallverdú M, Giraldo B, Benito S, Vázquez G, Voss A. Optimized symbolic dynamics approach for the analysis of the respiratory pattern. IEEE Transact. Biomed. Eng. 2005;52, (11):1832-9.

37. Baumert M, Walther T, Hopfe J, Stepan H, Faber R, Voss A. Joint symbolic dynamic analysis of beat-to-beat interactions of heart rate and systolic blood pressure in normal pregnancy. Med. Biol. Eng. Comput. 2002;40(2):241-5.

38. Baranowski R, Zebrowski JJ. Assessment of the RR versus QT relation by a new symbolic dynamics method. Gender differences in repolarization dynamics. Journ. Electrocardiol. 2002;35(2):95-103.

39. Rothberger CJ. Normale und pathologische physiologie der rhythmik und koordination des herzens. Ergebnisse der Physiologie. 1931;32(1):472-820.

40. Wessel N, Suhrbier A, Riedl M, Marwan N, Malberg H, Bretthauer G, Penzel T, Kurths J. Symbolic coupling traces for causality analysis of cardiovascular control. Conf. Proc. IEEE Eng. Med. Biol. Soc. 2011; pp. 5935-8.

41. Baier V, Baumert M, Caminal P, Vallverdú M, Faber R, Voss A. Hidden Markov models based on symbolic dynamics for statistical modeling of cardiovascular control in hypertensive pregnancy disorders. IEEE Trans. Biomed. Eng. 2006;53(1):140-3.

42. Babloyantz A, Destexhe A. Is the normal heart a periodic oscillator? Biol. Cybern. 1988;58(3):203-11.

43. Cysarz D, Lange S, Matthiessen PF, Leeuwen P. Regular heartbeat dynamics are associated with cardiac health. Amer. Journ. Physiol. Regul. Integr. Comp. Physiol. 2007;292(1):R368-R372.

44. Chon KH, Kanters JK, Cohen RJ, Holstein-Rathlou NH. Detection of "noisy" chaos in a time series. Meth. Inf. Med. 1997;36(4-5):294-7.

45. Lankhaar JW, Rövekamp FA, Steendijk P, Faes TJ, Westerhof BE, Kind T, Vonk-Noordegraaf A, Westerhof N. Modeling the instantaneous pressure-volume relation of the left ventricle: a comparison of six models. Ann. Biomed. Eng. 2009;37(9):1710-26.

46. Schäfer C, Plesser T, Abel HH. Methodik der Analyse binärer Sequenzen in der Herzfrequenz. Wien Med. Wochenschr. 1995;145(17-18):521-2.

47. Cysarz D, Bettermann H, Leeuwen P. Entropies of short binary sequences in heart period dynamics. Amer. Journ. Physiol. Heart Circ. Physiol. 2000;278(6):H2163-H2172.

48. Cysarz D, Van Leeuwen P, Edelhäuser F, Montano N, Porta A. Binary symbolic dynamics classifies heart rate variability patterns linked to autonomic modulations. Comput. Biol. Med. 2012;42(3):313-8.

49. Kolesnik VD, Mironchikov ET. Decoding of Cyclic Codes. Ohio:Wright-Patterson, AFB; 1973. 393 p.

50. Ornstein D. Bernoulli shifts with the same entropy are isomorphic. Adv. Math. 1970;4:337-52.

51. Wolfmann J. New bounds on cyclic codes from algebraic curves. Lecture Notes in Computer Science. 1989;388:47-62.

52. Diab M. New systolic architectures for cyclic code encoding. Lecture Notes in Computer Science. 1991;539:140-51.

53. Blahut RE. Cyclic Codes and Related Codes. In: Blahut RE. Algebraic Methods for Signal Processing and Communications Coding (Editor). 2011; pp. 57-69.

54. Greenough PP, Hill R. Optimal ternary quasi-cyclic codes. Designs, Codes and Cryptography. 1992;2(1):81-91.

55. Pei JY, Zhang XJ. Quaternary quasi-cyclic codes. Applied Mathematics. 2008;23(3):359-65.

56. Conan J, Seguin G. Structural properties and enumeration of quasi cyclic codes. Applicable Algebra in Engineering, Communication and Computing. 1993;4(1):25-39.

57. Feyziyev FG, Babavand AM. Description of decoding of cyclic codes in the class of sequential machines based on the Meggitt theorem. Automatic Control and Computer Sciences. 2012;46(4):164-9.

58. Seletkov VL. Variants of decoding of unsystematic cyclic codes. Radioelectronics and Communications Systems. 2013;56(5):260-4.

59. Shah T, Amanullah de Andrade AA. A method for improving the code rate and error correction capability of a cyclic code. Computational and Applied Mathematics. 2013;32(2):261-74.

60. Piva M, Sala M. A New Bound for Cyclic Codes Beating the Roos Bound. Lecture Notes in Computer Science. 2013;8080:101-12.

61. Edirisooriya G, Robinson JP. Cyclic code weight spectra and BIST aliasing. Journal of Electronic Testing. 1991;2(2):153-63.

62. Cammarota C, Rogora E. Spectral and symbolic analysis of heart rate data during the tilt test. Phys. Rev. E: Stat. Nonlin. Soft Mat. Phys. 2006;74(4):0429031-0429034.

63. Magagnin V, Bassani T, Bari V, Turiel M, Maestri R, Pinna GD, Porta A. Non-stationarities significantly distort short-term spectral, symbolic and entropy heart rate variability indices. Physiol. Measur. 2011;32(11):1775-86.

64. Liu YC, Hung CS, Wu YW, Lee YC, Lin YH, Lin C, Lo MT, Chan CC, Ma HP, Ho YL, Chen CH. Influence of non-alcoholic fatty liver disease on autonomic changes evaluated by the time domain, frequency domain, and symbolic dynamics of heart rate variability. PLOS ONE. 2013;8(4):1-6.

65. Perseguini NM, Takahashi AC, Rebelatto JR, Silva E, Borghi-Silva A, Porta A, Montano N, Catai AM. Spectral and symbolic analysis of the effect of gender and postural change on cardiac autonomic modulation in healthy elderly subjects. Braz. Journ. Med. Biol. Res. 2011;44(1):29-37.

66. Taşcă C, Stefăneanu L, Vasilescu C. The myocardial microangiopathy in human and experimental diabetes mellitus. (A microscopic, ultrastructural, morphometric and computer-assisted symbolic-logic analysis). Endocrinologie. 1986;24(2):59-69.

67. Saksena S, Craelius W, Hussain SM, Pantopoulos D, Parsonnet V. Intraoperative Spectral Analysis of Ventricular Potentials During Sinus Rhythm and Ventricular Tachycardia. Proc. of VIIth World Symposium on Cardiac Pacing Vienna. 1983; pp. 677-682.

68. Hongxuan Z, Yisheng Z, Yuhong X, Thakor NV. Pathological analysis of myocardial cell under ventricular tachycardia and fibrillation based on symbolic dynamics. Journ. Med. Eng. Technol. 2001;25(3):112-7.

69. Saeed M, Mark R. A novel method for the efficient retrieval of similar multiparameter physiologic time series using wavelet-based symbolic representations. Proc. of AMIA – 2006 Ann. Symp. pp. 679-83.

70. Peng CK, Yang AC, Goldberger AL. Statistical physics approach to categorize biologic signals: from heart rate dynamics to DNA sequences. Chaos. 2007;17(1):015115-1 – 015115-6.

71. Porta A, Tobaldini E, Guzzetti S, Furlan R, Montano N, Gnecchi-Ruscone T. Assessment of cardiac autonomic modulation during graded head-up tilt by symbolic analysis of heart rate variability. Am. Journ. Physiol. Heart Circ. Physiol. 2007;293(1):H702-H708.

72. Voss A, Schroeder R, Truebner S, Goernig M, Figulla HR, Schirdewan A. Comparison of nonlinear methods symbolic dynamics, detrended fluctuation, and Poincare plot analysis in risk stratification in patients with dilated cardiomyopathy. Chaos. 2007;17(1):015120-1 – 015120-7.

73. Tarkiainen TH, Kuusela TA, Tahvanainen KU, Hartikainen JE, Tiittanen P, Timonen KL, Vanninen EJ. Comparison of methods for editing of ectopic beats in measurements of short-term non-linear heart rate dynamics. Clin. Physiol. Funct. Imaging. 2007;27(2):126-33.

74. Sunita SM, Bhaaskaran VSK, Hegde D, Dhareshwar P. Error Detection and Correction in Embedded Memories Using Cyclic Code. Lecture Notes in Electrical Engineering. 2013;258:109-16.