УДК 616.12-008:004.891.3

Robust correlation dimension estimator for heart rate variability

A. Martynenko
V. N. Karazin Kharkiv National University, Ukraine
e-mail: Alexander.v.martynenko@karazin.ua

Abstract

Introduction. Non-linear methods of analysis have found widespread use in the Heart Rate Variability (HRV) technology, when the long-term HRV records are available. Using one of the effective nonlinear methods of analysis of HRV correlation dimension D2 for the standard 5-min HRV records is suppressed by unsatisfactory accuracy of available methods in case of short records (usually, doctors have about 500 RRs during standard 5-min HRV record), as well as complexity and ambiguity of choosing additional parameters for known methods of calculating D2.

The purpose of the work. Building a robust estimator for calculating correlation dimension D2 with high accuracy for limited series of RR-intervals observed in a standard 5-minute HRV record, i. e. with $N \approx 500$. As well as demonstrating the capabilities of the D2 formula on a well known attractors (Lorenz, Duffing, Hennon and etc.) and in applications for Normal Sinus Rhythm (NSR), Congestive Heart Failure (CHF) and Atrial Fibrillation (AF).

Materials and Methods. We used MIT-BIH long-term HRV records for normal sinus rhythm, congestive heart failure and atrial fibrillation. In order to analyze the accuracy of new robust estimator for D2, we used the known theoretical values for some famous attractors (Lorenz, Duffing, Hennon and etc.) and the most popular Grassberger-Procaccia (G-P) algorithm for D2.

The results of the study. We have shown the effectiveness of the developed D2 formula for time series of limited length ($N = 500 - 1000$) by some famous attractors (Lorenz, Duffing, Hennon and etc.) and with the most popular Grassberger-Procaccia (G-P) algorithm for D2. It was demonstrated statistically significant difference of D2 for normal sinus rhythm and congestive heart failure by standard 5 min HRV segments from MIT-BIH database. The promised technology for early prediction of atrial fibrillation episodes by current D2 algorithm was shown for standard 5 min HRV segments from MIT-BIH Atrial Fibrillation database.

Conclusion. Robust correlation dimension D2 estimator suggested in the article allows for time series of limited length ($N \approx 500$) to calculate D2 value that differs at mean from a precise one by $5 \pm 4\%$, as demonstrated for various well known attractors (Lorenz, Duffing, Hennon and etc.). We have shown on the standard 5-min segments from MIT-BIH database of HRV records:

- the statistically significant difference of D2 for cases of normal sinus rhythm and congestive heart failure;
- D2 drop significantly for the about 30 min. before of AF and D2 growth drastically under AF there was shown for HRV records with Atrial Fibrillation (AF) episodes.

The suggested robust correlation dimension D2 estimator is perfect suitable for real time HRV monitoring as accurate, fast and non-consuming for computing resources.

Key words: Hearth rate variability; Correlation dimension; Congestive heart failure; Atrial fibrillation.

ISSN 1812-7231 Klin. inform. telemed., 2020, vol. 15, iss. 16, pp. 62–68. https://doi.org/10.31071/kit2020.16.06
http://kit-journal.com.ua/en/index_en.html

References (19)

Introduction

The Heart Rate Variability (HRV) is based on measuring (time) intervals between R-peaks (of RR-intervals) of an electrocardiogram (ECG) and plotting a rhythmogram on their basis with its subsequent analysis by various mathematical methods that are classified as Time-Domain, Frequency-Domain and Nonlinear [1, 2]. Using nonlinear methods in HRV and ECG analysis has proven to be very advantageous, and they are reviewed in detail, for example, in [3, 4]. The newest review [5] showed the most applied for HRV nonlinear methods: Entropy (ApEn, SampEn, MSE), Dimensions (Fractal or Correlation dimension D2) and Plot analysis (Poincare, Recurrence). There are 263 numbers of papers and 10304 numbers of citations registered in the PubMed at 01/2019 for «Correlation Dimension in HRV or ECG» queries [5], – D2 is one of three tops nonlinear methods listed early. Applications of correlation dimension D2 for HRV of most cited papers are [5]: aging [6]; gender [6]; stress [7]; sleep [8]; arrhythmia [9]; heart transplantation [10]. Meanwhile, correlation dimension D2 for ECG has much more widespread medical applications [11]: atrial fibrillation, ventricular tachycardia, ventricular fibrillation, dilated cardiomyopathy, arrhythmias and sudden cardiac death. The high accuracy, sensitivity and specificity of D2 applications were shown in all cases [11]. This difference of correlation dimension D2 medical applications accruing for HRV and ECG explained by highly dependency of correlation dimension estimation on the length of the time series [12]. It is easy to retrieve a lot of ECG data points (N) in short medical examination but insufficiently in a standard 5-minute HRV record (usually $N \approx 300 - 600$). Generally the number of data points N necessary for estimation of correlation dimension D2 with good accuracy has upper bound [13]:

$$N \approx \sqrt{100^{D_2} e^{\tau h_2 D_2}}, \quad (1)$$

where h_2 – correlation entropy; τ – time delay of the reconstruction;
and lower bound while entropy factor can be ignored [14]:

$$N \approx 42^{D_2}. \quad (2)$$

So, we can easily estimate for normal sinus rhythm (D2 about 2.0) at least 1764 data points (RRs intervals) are necessary that is about 3 times more than doctors have during standard 5-min HRV examination. In case of arrhythmias or atrial fibrillation, when D2 grow up to 8–10, the number of necessary N can be a hundred thousand RRs. That is possible to accrue only by daily Holter monitoring (ECG or HRV) and has heavy computation consumption for D2 calculations.

The purpose of current article is to suggest robust correlation dimension D2 estimator for short time series (e. g. $N \approx 500$ as for standard 5-min HRV record) with good accuracy, fast calculations and low consumptions of compute resources. It is possible to make it suitable for real time HRV monitoring and widen for standard 5-min HRV records.

Materials and Methods

We used long-term HRV records by Massachusetts Institute of Technology – Boston's Beth Israel Hospital (MIT-BIH) from [15] (http://www.physionet.org), a free-access, on-line archive of physiological signals. Normal Sinus Rhythm (NSR) RR Interval Database includes beat annotation files for 54 long-term ECG recordings of subjects in normal sinus rhythm (30 men, aged 28.5 to 76, and 24 women, aged 58 to 73). Congestive Heart Failure (CHF) RR Interval Database includes beat annotation files for 29 long-term ECG recordings of subjects aged 34 to 79, with congestive heart failure (NYHA classes I, II, and III). Subjects include 8 men and 2 women; gender of the remaining 21 subjects is not known. The original electrocardiography (ECG) signals for both NSR and CHF RR interval databases were digitized at 128 Hz, and the beat annotations were obtained by automated analysis with manual review and correction. The MIT-BIH Atrial Fibrillation (AF) Database [16] was used for Correlation Dimension D2 analyzing with long and short RR's subsets. This database includes 25 long-term ECG recordings of human subjects with atrial fibrillation (mostly paroxysmal). The individual recordings are each 10 hours in duration, and contain two ECG signals each sampled at 250 samples per second with 12-bit resolution over a range of ±10 millivolts. The original analog recordings were made at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) using ambulatory ECG recorders with a typical recording bandwidth of approximately 0.1 Hz to 40 Hz.

Let us consider time series $X = \{x_1, x_2, \dots x_n\}$ with N elements which in HRV analysis will be the RR interval series with N being the total number of beats. The goal of time-series analysis is to learn about the dynamics behind observed time-ordered data. Correlation dimension D2 measures the degree of complexity of the system that generates the time series [12] and estimates the number of independent variables governing the behavior of the dynamical system. The Grassberger-Procaccia (G-P) algorithm for D2 calculations is the most popular for now and shows very good accuracy if obey the requirements for number of necessary data points (1)–(2). G-P has pure accuracy in case of limited data series and inapplicable for standard 5-min HRV records (tab. 1).

Let us define two invariants of isometric transformations of the time series in order to construct new robust D2 estimator:

1. The length of times series polygonal chain λ

$$\lambda = \sum_{i=0}^{N-1} \sqrt{1 + (x_{i+1} - x_i)^2}, \quad (3)$$

2. Chirality of time series χ (asymmetry about the mean)

Let's define two elements subset $A = \{a, b\}$ with Euclidian metric L2. Each element of subset A is the difference between two nearby observations of X: $a_i = x_{i+1} - x_i$; $b_i = x_i - x_{i-1}$. Let us construct a separable system A^+ and A^- from the elements of A:

$$A^+ = \{|a+b|, |a-b|\};\ A^- = -A^+;$$

where for all x_i taking an extreme value in the triple x_{i+1}, x_i, x_{i-1}

$$\forall x_i \left(x_{i+1} > x_i < x_{i-1}\right) \overset{\min(x_i)}{\Rightarrow} |a+b|;$$

$$\forall x_i \left(x_{i+1} < x_i > x_{i-1}\right) \overset{\max(x_i)}{\Rightarrow} -|a+b|;$$

where for all x_i which is not taking an extreme value in the triple x_{i+1}, x_i, x_{i-1} it is necessary to make minimal rotation to satisfy the extremality condition of x_i

$$\forall x_i \left(x_{i+1} > x_i > x_{i-1} \,\&\, |x_{i+1} - x_i| > |x_i - x_{i-1}|\right) \overset{\min(x_i)}{\Rightarrow}$$
$$\overset{\min(x_i)}{\Rightarrow} |a+b-2(x_i - x_{i-1})| = |a-b|;$$

$$\forall x_i \left(x_{i+1} < x_i < x_{i-1} \,\&\, |x_{i+1} - x_i| < |x_i - x_{i-1}|\right) \overset{\min(x_i)}{\Rightarrow}$$
$$\overset{\min(x_i)}{\Rightarrow} |a+b-2(x_{i+1} - x_i)| = |a-b|;$$

$$\forall x_i \left(x_{i+1} < x_i < x_{i-1} \,\&\, |x_{i+1} - x_i| > |x_i - x_{i-1}|\right) \overset{\max(x_i)}{\Rightarrow}$$
$$\overset{\max(x_i)}{\Rightarrow} -|a+b-2(x_i - x_{i-1})| = -|a-b|;$$

$$\forall x_i \left(x_{i+1} > x_i > x_{i-1} \,\&\, |x_{i+1} - x_i| < |x_i - x_{i-1}|\right) \overset{\max(x_i)}{\Rightarrow}$$
$$\overset{\max(x_i)}{\Rightarrow} -|a+b-2(x_{i+1} - x_i)| = -|a-b|\ .$$

Counting over all elements A, we determine the degree of chirality of time series χ:

$$\chi = \sum_{N-2} \left\{A^+, A^-\right\}. \quad (4)$$

Finally, we express the value of the correlation dimension D2 in terms of the two introduced invariants λ and χ, as a function of the ratio of the degree of symmetry breaking of the time series per unit length of the polygonal chain:

$$D2 = 2e^{\frac{\pi}{2} tanh(4\pi \frac{\chi}{\lambda})}. \quad (5)$$

The best result in accuracy is obtained when the separable system A^+ and A^- is constructed from normalized elements with the norm $\|A\|$:

$$A^+ = \{\frac{|a+b|}{\|A\|}, \frac{|a-b|}{\|A\|}\};\ A \ \ = -A^+.$$

Results and Discussion

First of all we need to estimate the accuracy of suggested formula (5) and its dependency from time series length. We compare in Table 1. the results of calculations for correlation dimension D2 by formula (5), G-P algorithm and theoretical values for the some famous attractors.

The suggested robust correlation dimension D2 estimator (5) in compare with theoretical D2 for some famous attractors has shown mean error at 5% for $N = 500$, 3% for $N = 1000$ and 1% for N=10000; the G-P algorithm does not convergence for $N = 500$ and show mean error for D2 estimation at 126% for $N = 1000$ and 2% for $N = 10000$. We can make a conclusion about good quality of correlation dimension D2 estimator (5) for D2 analyzing of standard 5-min HRV record.

Now we can analyze different RR records from MIT-BIH database for short subsets only.

In tab. 2 we use MIT-BIH RR data for Normal and CHF groups and compare qualitative reactions in different groups for two nonlinear indexes, – Entropy (*EnRE* [19]) and Correlation dimension D2 (5). The same qualitative behavior was shown in all cases: both *EnRE* [19] and D2 (5) show significant drop for CHF group in compare with Normal group; for Normal group no significant differences between Men aged less 50 y.o., Men aged older 60 y.o. and Women aged older 60 y.o. This is exactly what was expected for these nonlinear indexes in examined groups.

The MIT-BIH Atrial Fibrillation (AF) Database with 10-hours records was divided for $N = 500$ subsets and researched for Correlation Dimension D2 evolution before AF episodes and during AF.

Fig. 1 shows typical pattern of correlation dimension D2 evolution before atrial fibrillation episode: each epoch on the fig. 1. consists of short RRs records ($N = 500$); epoch with # '0' is the beginning of AF according to MIT-BIH reference rhythm annotations. Correlation dimension D2 does not have significant difference from mean record value under Normal rhythm intervals except 5–6 epochs before and after AF episodes. The D2 significantly drop for about 30 minutes (or 5–6 epoch by $N = 500$ RRs) before AF: D2 drop shown from epoch # '–5' on the fig. 1. During AF the D2 growth 4–5 times over the mean value. This is the clue for real time automatic AF prediction for the about 30 minutes before AF episodes.

Conclusions

Correlation dimension D2 estimator (5) suggested in the article allows for time series of a limited length ($N = 500$) to find D2 value with high accuracy $M = 5 \pm 4\%$, which has been demonstrated for some famous attractors with known theoretical D2 values

Tab. 1. Comparison of proposed estimator (5) and Grassberger–Procaccia algorithm for different time series length and theoretical correlation dimension D2 values for attractors.

Attractor	Grassberger–Procaccia algorithm, D2			Robust D2 estimator (5), D2		
	N=500	N=1000	N=10000	N=500	N=1000	N=10000
Duffing, D2 = 2,3	N/A	2,12 Err=8%	2,38 Err=3%	2,20 Err=9%	2,22 Err=3%	2,29 Err=0%
Lorenz, D2=2,02	N/A	2,94 Err=46%	2,10 Err=4%	2,01 Err=0%	2,03 Err=0%	2,02 Err=0%
Hennon, D2=1,25	N/A	7,12 Err=484%	1,23 Err=1%	1,36 Err=9%	1,15 Err=8%	1,25 Err=0%
Logistic, D2= 8,2	N/A	1,07 Err=89%	8,21 Err=0%	8,56 Err=4%	8,25 Err=1%	8,05 Err=2%
Rossler, D2=1,99	N/A	1,95 Err=2%	1,91 Err=4%	2,05 Err=3%	2,04 Err=3%	2,03 Err=2%
Mean Err ± SD	N/A	126±203%	2±2%	5±4%	3±3%	1±1%

Tab. 2. Entropy EnRE [19] and correlation dimension D2 (5) for MIT–BIH Normal group and Congestive Heart Failure group.

Test		Entropy EnRE [19] N=500		Correlation dimension D2 (5) N=500	
		Mean±SD	Reaction	Mean±SD	Reaction
MIT-BIH RR database	Normal	1,72±0,47	Significantly drop (p<0,05)	2,10±0,28	Significantly drop (p<0,05)
	CHF	0,65±0,76		1,93±0,22	
MIT-BIH	Men<50 y.o.	1,73±0,33	Difference insignificant	2,24±0,49	Difference insignificant
Normal group	Men>60 y.o.	1,70±0,55		2,08±0,18	
	Women>60 y.o.	1,78±0,51		2,05±0,25	

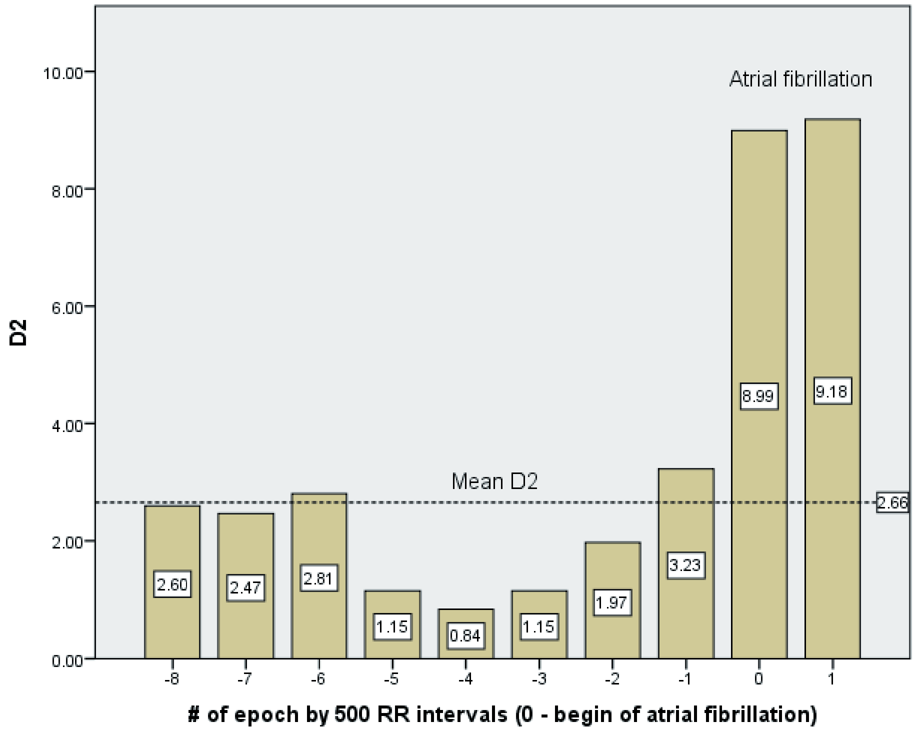

Fig. 1. Typical pattern of Correlation Dimension D2 (5) before atrial fibrillation episode (MIT–BIH AF Database [16]).

(tab. 1). The accuracy of correlation dimension D2 estimator (5) for big chunks of data ($N = 10000$) is about the same as for well known and popular Grassberger-Procaccia algorithm (tab. 1).

Using the proposed correlation dimension D2 estimator (5) for MIT-BIH database of HRV records, we show for short records ($N = 500$) in compare with Entropy (*EnRE* [19]) for classification of Normal Sinus Rhythm (NSR) and Congestive Heart Failure (CHF) cases (tab. 2). It demonstrated the same qualitative behavior for all cases: both *EnRE* [19] and D2 (5) shows significant drop for CHF group in compare with Normal group; for Normal group no significant differences between Men aged less 50 y.o., Men aged older 60 y.o. and Women aged older 60 y.o. This is exactly that was expected for these nonlinear indexes in examined groups.

The MIT-BIH Atrial Fibrillation (AF) Database records was divided for a short epochs ($N = 500$) and researched for correlation dimension D2 evolution before AF episodes and during AF. Correlation dimension D2 does not have significant difference from mean record value during Normal rhythm intervals except 5–6 epochs before and after AF episodes (fig. 1). The D2 significantly drop about for 30 minutes before AF and drastically growth under AF (fig. 1). This is the clue for real time automatic AF prediction for the about 30 minutes before AF episodes.

Let us summarize:

1) the new approach for correlation dimension D2 estimator was suggested in (5);

2) formula (5) is based on two introduced invariants λ (3) and χ(4), as a function of the ratio of the degree of symmetry breaking of the time series per unit length of the polygonal chain;

3) the accuracy of correlation dimension D2 estimator (5) was shown by the some famous attractors in the wide diapason of time series length ($N = 500 - 10000$);

4) qualitative behavior correlation dimension D2 estimator (5) and Entropy (*EnRE* [19]) are the same for the groups of Normal Sinus Rhythm (NSR) and Congestive Heart Failure (CHF). It is shown significant difference between NSR and CHF groups for both;

5) D2 significantly drop for the about 30 minutes before Atrial Fibrillation (AF). This is the clue for real time automatic AF prediction for the about 30 minutes before AF episodes (fig. 1).

6) the suggested robust correlation dimension D2 estimator (5) is perfect suitable for real time HRV monitoring as accurate, fast and non-consuming for computing resources.

The studies were carried out in compliance with international bioethical standards and the provisions of the Helsinki Declaration (as amended in 2013). The author of the article, A. Martynenko, confirm that they have no conflict of interest.

References

1. Task force of the European society of cardiology and the North American society of pacing and electrophysiology. Heart rate variability — standards of measurement, physiological interpretation, and clinical use. *Circulation,* 1996, vol. 93, iss. 5, pp. 1043–1065.
2. Yabluchansky N., Martynenko A. *Variabel'nost' serdechnogo ritma dlya klinicheskoy praktiki* [Heart Rate Variability for clinical practice]. 2010. Kharkiv, Univer. Press, 131 p. (In Russ.). http://dspace.univer.kharkov.ua/handle/123456789/1462.
3. Nayak S. K. at all. A Review on the Nonlinear Dynamical System Analysis of Electrocardiogram *Signal. J. Health. Eng.* 2018; 2018: 6920420. doi: 10.1155/2018/6920420.
4. De Godoy M. F. Nonlinear Analysis of Heart Rate Variability: A Comprehensive Review. *J. Cardiology and Therapy,* 2016, vol. 3, no. 3, pp. 528–533.
5. Henriques T., Ribeiro M., Teixeira A., Castro L., Antunes L. and Costa-Santos C. Nonlinear Methods Most Applied to Heart-Rate Time Series: A Review. *Entropy* 2020, iss. 22, p. 309; doi:10.3390/e22030309.
6. Beckers F., Verheyden B., Aubert A. E. Ageing and non-linear heart rate control in a healthy population. *Am. J. Physiol.-Heart Circ. Physiol.,* 2006, iss. 290, pp. H2560–H2570.

7. Melillo P., Bracale M., Pecchia L. Nonlinear heart rate variability features for real-life stress detection. Case study: Students under stress due to university examination. *Biomed. Eng. Online,* 2011, iss. 10, p. 96.
8. Acharya U. R., Chua E. C. P., Faust O., Lim T. C., Lim L. F. B. Automated detection of sleep apnea from electrocardiogram signals using nonlinear parameters. *Physiol.* Meas., 2011, iss. 32, p. 287.
9. Owis M. I., Abou-Zied A. H., Youssef A. B., Kadah Y. M. Study of features based on nonlinear dynamical modeling in ECG arrhythmia detection and classification. *IEEE Trans. Biomed. Eng.,* 2002, vol. 49, pp. 733–736.
10. Guzzetti S., Signorini M.G., Cogliati C., Mezzetti S., Porta A., Cerutti S., Malliani A. Non-linear dynamics and chaotic indices in heart rate variability of normal subjects and heart-transplanted patients. *Cardiovasc. Res.*, 1996, vol. 31, pp. 441–446.
11. Nayak S. K., Bit A., Dey A., Mohapatra B. and Pal K. A Review on the Nonlinear Dynamical System Analysis of Electrocardiogram Signal. *Hindawi J. Healthcare Engineering,* 2018, Article ID 6920420, 19 p. https://doi.org/10.1155/2018/6920420.
12. Grassberger P. and Procaccia I., Characterization of strange attractors, *Physical Review Letters,* 1983, vol. 50, no. 5, pp. 346–349. doi: 10.1103/PhysRevLett.50.346
13. Olbrich E. and Kantz H., Inferring chaotic dynamics from time series: On which length scale determinism becomes visible, *Physics Letters A*, 1997, iss. 232, pp.63–69.
14. Smith L., Intrinsic limits on dimension calculations, *Physics Letters A,* 1988, iss. 133, pp.283–288.
15. Goldberger A., Amaral L., Glass L., Hausdorff J., Ivanov P. C., Mark R., Stanley H. E. Physio Bank, Physio Toolkit, and Physio Net: Components of a new research resource for complex physiologic signals. *Circulation* [Online], 2000, vol.23, iss. 101, pp. e215–e220.
16. Moody G.B., Mark R.G. A new method for detecting atrial fibrillation using R-R intervals. *Computers in Cardiology*. 1983, no. 10, pp. 227–230.
17. Lorenz E. N. Deterministic nonperiodic flow. *J. Atmos. Sci.,* 1963, no. 20, pp. 130–141. https://doi.org/10.1175/1520-0469(1963)020<0448:TMOV<2.0.CO;2.
18. Henon M. A two-dimensional mapping with a strange attractor. *Commun. Math. Phys.*, vol. 50, pp. 69–77. https://doi.org/10.1007/BF01608556.
19. Martynenko A., Raimondi G., Budreiko N. Robust Entropy Estimator for Heart Rate Variability. *J. Clinical Informatics and Telemedicine,* 2019, vol. 14, iss. 15, pp. 67–73. DOI: https://doi.org/10.31071/kit2019.15.06

Corresponding author

Professor **Alexander V. Martynenko**, PhD, D.Sc.
V. N. Karazin Kharkiv National University, School of Medicine,
Svobodi Sq., 4, Kharkiv, 61022, Ukraine
tel.: +380 97 248 1436
e-mail: Alexander.v.martynenko@karazin.ua

Робастна формула кореляційної розмірності для аналізу варіабельності серцевого ритму

О. В. Мартиненко

Харківський національний університет імені В. Н. Каразіна, Україна

Резюме

Вступ. Нелінійні методи аналізу знайшли широке застосування в технології варіабельності серцевого ритму (ВСР) при наявності довгих записів ВСР. Використання одного з ефективних методів нелінійних аналізу ВСР, — кореляційної розмірності D2 для 5-хв. записів ВСР стримується незадовільною точністю наявних методів в разі коротких записів (зазвичай, стандартна 5 хв. запис ВСР містить 300–600 комплексів RR), а також складністю і неоднозначністю вибору додаткових параметрів для відомих методів обчислення кореляційної розмірності D2.

Мета роботи. Побудувати робастну формулу обчислення кореляційної розмірності D2 з високою точністю для обмеженого ряду RR-інтервалів, які спостерігаються в стандартній 5-хвилинного запису ВСР. А також продемонстровані можливості запропонованої формули D2 на прикладі добре відомих атракторів (Лоренца, Даффінга, Хеннона і ін.) і в медичних додатках для нормального серцевого ритму, серцевої недостатності та фібриляції передсердь.

Матеріали та методи. У статті була використана база даних MIT-BIH з тривалими записами ВСР в разі нормального синусового ритму (NSR), при серцевій недостатності (CHF) і фібриляції передсердь (AF). Щоб проаналізувати точність нової робастної оцінки кореляційної розмірності D2, ми використовували відомі теоретичні значення для деяких відомих атракторої (Лоренца, Даффінга, Хеннон і ін.) і порівняння з найбільш популярним алгоритмом Грассбергера-Прокаччі.

Результати. Була показана ефективність розробленої формули D2 для часових рядів обмеженої довжини ($N = 500 - 1000$) на прикладі відомих атракторів (Лоренца, Даффінга, Хеннон і ін.) і за допомогою найбільш популярного алгоритму Грассбергера-Прокаччі. Було продемонстрована статистично значуща відмінність D2 для нормального синусового ритму та серцевої недостатності для стандартних 5-хвилинних сегментів з бази даних MIT-BIH записів ВСР. За допомогою запропонованого алгоритму D2 була показана можливість раннього передбачення епізодів фібриляції передсердь на стандартних 5-хвилинних сегментах з бази даних MIT-BIH записів ВСР.

Висновки. У статті пропонується робастна формула для обчислення кореляційної розмірності D2. Вона дозволяє для часових рядів обмеженої довжини ($N \approx 500$) знаходити значення D2, яке в середньому відрізняється від точного на $5 \pm 4\%$, що продемонстровано для різних добре відомих атракторах (Лоренц, Даффінг, Хеннон і ін.). На стандартних 5-хвилинних сегментах з бази даних MIT-BIH записів ВСР ми показали статистично значущу відмінність D2 для випадків нормального синусового ритму та серцевої недостатності; для записів ВСР з епізодами фібриляції передсердь (AF) було показано, що D2 значно знижується приблизно за 30 хв. перед AF і різко зростає при AF. Пропонована робастна формула для розрахунку кореляційної розмірності D2 ідеально підходить для моніторингу ВСР в реальному часі, оскільки дозволяє швидко і практично без витрат обчислювальних ресурсів знаходити D2 з високою точністю.

Ключові слова: варіабельність серцевого ритму; кореляційний розмірність; серцева недостатність; фібриляція передсердь.

Робастная формула корреляционной размерности для анализа вариабельности сердечного ритма

А. В. Мартыненко

Харьковский национальный университет имени В. Н. Каразина, Украина

Резюме

Введение. Нелинейные методы анализа нашли широкое применение в технологии вариабельности сердечного ритма (ВСР) при наличии длинных записей ВСР. Использование одного из эффективных методов нелинейных анализа ВСР, — корреляционной размерности D2 для 5-мин. записей ВСР сдерживается неудовлетворительной точностью имеющихся методов в случае коротких записей (обычно, стандартная 5 мин. запись ВСР содержит 300–600 комплексов RR), а также сложностью и неоднозначностью выбора дополнительных параметров для известных методов вычисления корреляционной размерности D2.

Цель работы. Построить робастную формулу вычисления корреляционной размерности D2 с высокой точностью для ограниченного ряда RR-интервалов, наблюдаемых в стандартной 5-минутной записи ВСР. А также продемонстрированы возможности предложенной формулы D2 на примере хорошо известных аттракторов (Лоренца, Даффинга, Хеннона и др.) и в медицинских приложениях для нормального сердечного ритма, сердечной недостаточности и фибрилляции предсердий.

Материалы и методы. В статье была использована база данных MIT-BIH с продолжительными записями ВСР в случае нормального синусового ритма (NSR), при сердечной недостаточности (CHF) и фибрилляции предсердий (AF). Чтобы проанализировать точность новой робастной оценки корреляционной размерности D2, мы использовали известные теоретические значения для некоторых известных аттракторов (Лоренца, Даффинга, Хеннона и др.) и сравнения с наиболее популярным алгоритмом Грассбергера-Прокаччи.

Результаты. Была показана эффективность разработанной формулы D2 для временных рядов ограниченной длины ($N = 500 - 1000$) на примере теоретических значений для известных аттракторов (Лоренца, Даффинга, Хеннона и др.) и с помощью наиболее популярного алгоритма Грассбергера-Прокаччи. Было продемонстрировано статистически значимое различие D2 для нормального синусового ритма и сердечной недостаточности для стандартных 5-минутных сегментов из базы данных MIT-BIH записей ВСР. С помощью предложенного алгоритма D2 была показана возможность раннего предсказания эпизодов фибрилляции предсердий на стандартных 5-минутных сегментах из базы данных MIT-BIH записей ВСР.

Выводы. В статье предлагается робастная формула для вычисления корреляционной размерности D2. Она позволяет для временных рядов ограниченной длины ($N \approx 500$) находить значение D2, которое в среднем отличается от точного на 5 ± 4%, что продемонстрировано для некоторых хорошо известных аттракторов (Лоренца, Даффинга, Хеннона и др.). На стандартных 5-минутных сегментах из базы данных MIT-BIH записей ВСР мы показали статистически значимое различие D2 для случаев нормального синусового ритма и сердечной недостаточности; для записей ВСР с эпизодами фибрилляции предсердий (AF) было показано, что D2 значительно снижается примерно за 30 мин. перед AF и резко возрастает при AF. Предлагаемая робастная формула для расчета корреляционной размерности D2 идеально подходит при мониторинге ВСР в реальном времени, поскольку позволяет быстро и практически без затрат вычислительных ресурсов находить D2 с высокой точностью.

Ключевые слова: вариабельность сердечного ритма; корреляционная размерность; сердечная недостаточность; фибрилляция предсердий.