Nonlinear dynamics methods in the analysis of the heart rate variability

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Abstract

Purpose: **We analyzed the heart rate variability (RR intervals) by means of nonlinear dynamics methods: Poincaré plot (return map), approximate entropy (ApEn) and detrended fluctuation analysis (DFA). The purpose of this study was the quantitative and qualitative assessment of heart rate variability by means of these nonlinear dynamics methods.**

Material and methods: **The Poincaré plot is a scattergram, which is constructed by plotting each RR interval against the previous one. Approximate entropy describes the complexity and irregularity of the signals. Detrended fluctuation analysis quantifies fractal-like correlation properties of the data.**

We analyzed two groups of patients: test group A – 15 diabetic children with diabetes type 1 and microalbuminuria and control group C – 24 healthy children. For each patient 24 hour ECG (RR intervals) was recorded. Statistical analysis was performed by means of nonparametric Mann-Whitney test.

Results: **Return maps of healthy children are mostly very complex. In the case of diabetic children we found torpedo-shaped plots. The values of ApEn were lower in diabetic children that indicated more regular heart rate in these patients. DFA method shows also differences between the investigated groups.**

Conclusions: **We concluded that using nonlinear dynamics methods we could quantitatively and qualitatively study the heart rate variability in healthy and diabetic patients.**

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Key words: ECG signal processing, heart rate variability, Poincaré plot, approximate entropy, detrended fluctuation analysis.

Introduction

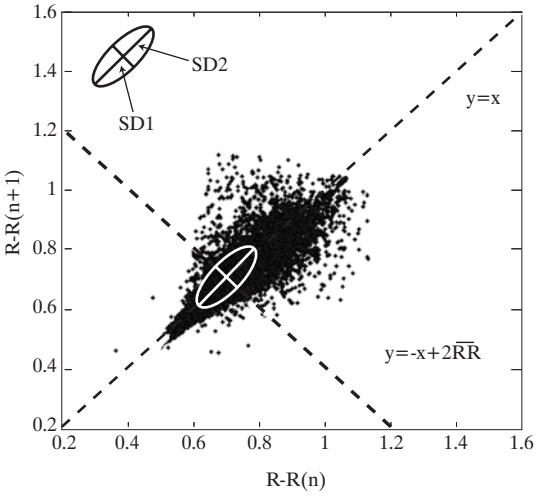
The analysis of heart rate variability is based mainly on analysis of RR intervals [1]. RR intervals are the series of time intervals between heartbeats [2]. We can observe RR intervals in electrocardiogram, which is simply graphic representation of the electrical forces produced by the heart [3].

The Poincaré plot (return map) is a scattergram, which is constructed by plotting each RR interval against the previous one [4]. The Poincaré plot may be analyzed quantitatively by fitting an ellipse to the plotted shape [5] (*Fig. 1*). The center of the ellipse is determined by average RR interval. SD1 means the standard deviation of the distances of points from y = x axis, SD2 means the standard deviation of the distances of points from $y=-x+\overline{RR}$ axis, where $\overline{RR}$ is the average R-R interval [6]. SD1 (instantaneous beat-to-beat variability of the data) determines the width of the ellipse, SD2 (continuous beat-to-beat variability) determines the length of the ellipse [7]. The ratio SD1/SD2 is the measure of heart activity.

Approximate entropy (ApEn) describes the complexity and irregularity of the signal [8,9]. ApEn is low in regular time series and high in complex irregular ones. It can be applied to both deterministic and stochastic signals and their combinations.

Detrended fluctuation analysis (DFA) quantifies fractal-like correlation properties of the data [10]. The root-mean square fluctuation of the integrated and detrended data are measured in observation box of various sizes and then plotted against the size of the box [11]. The scaling exponent represents the slope of this line, which relates log(F(n)-fluctuation) to log(n-box size). The short-term (F-fast) and long-term (S-slow) scaling exponents are also calculated [12].

Figure 1. **Return map of RR intervals with fitted ellipse to the plotted shape. SD1 means the standard deviation of the distances of points from y=x axis, SD2 means the standard deviation of the distances of points from y=-x+$2\overline{RR}$ axis. SD1 and SD2 determine the width and length of the fitted ellipse.**



Material and methods

We analyzed two groups of patients: test group A – 15 diabetic children with diabetes type 1 and microalbuminuria and control group C – 24 healthy children. For each patient 24 hour ECG was recorded. ECG records were divided into two segments, day (06:00 to 22:00) and night activity (22:00 to 06:00), respectively (A_{night}, $A_{day,}$ $C_{night,}$ C_{day}).

Programs written in Matlab (MathWorks Inc., USA), a high performance language for technical computing, were used to analyze the ECG signals. The SD1/SD2 ratio, the approximate entropy and DFA parameters were calculated. Statistical analysis was performed by means of nonparametric Mann-Whitney test for unpaired data.

Results

Return maps of healthy patients are mostly very complex. In the case of diabetic children we found (in most cases) torpedo-shaped plot. *Tab. 1* shows the mean values of SD1/SD2 ratio, approximate entropy and DFA exponents for groups: A_{night}, $A_{day,}$ $C_{night,}$ $C_{day.}$ The results are tabulated in the form mean ±standard deviation.

The values of ApEn were lower in diabetic children that indicated more regular heart rate in these patients. DFA method shows also differences between studied groups of patients.

Statistical analysis was performed between the following pairs of groups: A_{night} – C_{night} and A_{day} – C_{day} (*Tab. 2*). Approximate entropy values and long-term scaling exponents did not differ between A_{day} and C_{day} groups ($p>0.05$). Also long-term scaling exponents did not differ between A_{night} and C_{night} groups ($p> 0.05$). In other cases we found statistical significant differences between investigated groups of patients.

Table 1. **SD1/SD2 ratio, approximate entropy and detrended fluctuation analysis exponents in the studied groups**

Group	SD1/SD2 ratio	ApEn	DFA (Slow)	DFA (Fast)
A_{night}	0.257±0.079	1.344±0.152	1.053±0.105	1.034±0.179
A_{day}	0.175±0.044	0.997±0.190	0.984±0.072	1.273±0.141
C_{night}	0.396±0.130	1.454±0.153	1.002±0.124	0.896±0.176
C_{day}	0.231±0.069	1.112±0.186	0.984±0.060	1.145±0.158

Table 2. **Results of statistical analysis of investigated groups**

	SD1/SD2ratio		ApEn		DFA (Slow)		DFA (Fast)	
Groups	C_{night}	C_{day}	C_{night}	C_{day}	C_{night}	C_{day}	C_{night}	C_{day}
A_{night}	0.0004*		0.042*		0.279		0.045*	
A_{day}		0.019*		0.103		0.806		0.029*

*statistically significant differences ($p<0.05$)

Conclusions

We concluded that using nonlinear dynamics methods we could quantitatively and qualitatively study the heart rate variability in healthy and diabetic children.

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