

ORIGINAL ARTICLE

Complex measurements of heart rate variability in obese youths: distinguishing autonomic dysfunction

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Abstract

Introduction: Heart rate variability (HRV) can be assessed from RR-intervals. These are derived from an electrocardiographic PQRST-signature and can deviate in a chaotic or irregular manner. In the past, techniques from statistical physics have allowed researchers to study such systems.

Objective: This study planned to assess the heart rate dynamics in young obese subjects by nonlinear metrics to heart rate variability.

Method: 86 subjects were split equally according to status. Heart rate was recorded with the subjects resting in a dorsal (prone) position for 30 minutes. The complexity of the RR-intervals was assessed by five Entropies, Detrended Fluctuation Analysis, Higuchi and Katz's fractal dimensions. Following inconclusive tests of normality we calculated the One-Way Analysis of Variance, Kruskal-Wallis, and the Effect Sizes by Cohen's d significances.

Results: It was established that Shannon, Renyi and Tsallis Entropies and the Higuchi and Katz's fractal dimensions could significantly discriminate the two groups. The three entropies were higher in obese youths, suggesting less predictable sets of RR intervals ($p < 0.0001$; $d \approx 1.0$). Whilst the Higuchi ($p < 0.003$; $d \approx 0.76$) and Katz's ($p \approx 0.02$; $d \approx 0.57$) fractal dimensions were lower in obese youths.

Conclusion: As with chaotic globals an increase in response was detected by three measures of entropy in young obese. This is counter to the decreasing response detected by fractal dimensions. Chaotic globals and entropies are more dependable than fractal dimensions when assessing the responses to obesity.

Keywords: youth obesity, detrended fluctuation analysis, entropy, fractal dimensions

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INTRODUCTION

Heart rate variability (HRV) can be assessed from RR-intervals^{1,2}. These are derived from an electrocardiographic PQRST-signature and can deviate in a chaotic or irregular manner. In the past, techniques from statistical physics^{3,4} have allowed researchers to study such systems⁵.

HRV is an inexpensive, reliable and non-invasive technique to monitor the sympathetic and parasympathetic components of the autonomic nervous system (ANS)⁶. HRV is highly regarded as a functional marker of human development⁷. It can be enforced to identify phenomena related to the ANS in healthy subjects and patients with certain diseases, such as diabetes mellitus^{8, 9}, chronic obstructive pulmonary disorder (COPD)¹⁰, epilepsy^{11,12} and those referred to as “dynamical diseases¹³.”

Previously, we have assessed datasets through chaotic globals in obese youths¹⁴. These techniques are useful since they can be applied straightforwardly to entire and in particular short time-series (20 minutes) to achieve statistically significant responses. So far, these techniques are formulated by enforcing either Welch¹⁵ or Multi-Taper Method^{16,17} (MTM) power spectra, so the phase information is lost. This provides the motivation to assess these datasets of obese youths by alternative complex measures. In this study we enforce five based on entropy: Approximate¹⁸, Sample^{19,20}, Shannon²¹, Renyi^{22,23} and Tsallis²⁴ Entropies and then, the Detrended Fluctuation Analysis (DFA)²⁵. Furthermore, we then assessed the same data using the Higuchi²⁶ and Katz’s²⁷ fractal dimensions.

METHODS & STATISTICAL ANALYSES

Patient Selection and assessments were exactly as the study by Vanderlei *et al*¹⁴.

Shannon entropy

Shannon Entropy²¹ is a measure of lack of knowledge. A low entropy dataset is highly predictable - whereas a high entropy dataset is less predictable. In contrast to Tsallis and Renyi entropies (discussed next), Shannon entropy is additive. Hence, if the probabilities can be factorised into independent factors, the entropy of the joint process is the sum of the entropies of the separate processes.

Renyi entropy

The order-q Renyi entropies²² are a series of entropy like quantities. When the entropic order $\alpha \rightarrow 1$, Renyi entropy coincides with Shannon entropy; which can be derived by the l’Hospital’s rule^{28,29}. Here we set the entropic order $\alpha=0.25$. As entropic order increases the measures become more sensitive to the values occurring at higher probabilities and less to those of lower probabilities. Renyi entropy is described fully in studies by Zyczkowski²³.

Tsallis entropy

Tsallis entropy²⁴ is a generalisation of the standard Shannon-Boltzmann-Gibbs entropy. It was introduced as a basis for generalising the standard statistical mechanics.

Where entropic index, $q \rightarrow 1$ it is the Shannon-Boltzmann-Gibbs entropy. Here we set entropic index, $q=0.25$. Tsallis entropy is discussed further in the publications by dos Santos³⁰ and, Plastino and Plastino³¹.

Detrended fluctuation analysis (DFA)

DFA²⁵ can be applied to datasets where statistics such as mean, variance and autocorrelation vary with time. DFA is a technique quantifying how the fluctuations of a signal scale with the number of samples of that signal. Regarding DFA according to Donaldson³² the time-series of length k was manipulated as follows.

$$y(k) = \sum_{i=1}^k (RR(i) - \text{mean}(RR))$$

The integrated time-series was then divided into equally sized and non overlapping windows of length w . A linear regression line was fitted through the data in each window and the time-series manipulated by subtracting the regression line from the data. The root mean square fluctuation $F(w)$ of the integrated and detrended time-series defined as

$$F(w) = \sqrt{\frac{1}{N} \sum_{k=1}^N [y(k) - y_w(k)]^2}$$

The scaling exponent is obtained as the slope of the straight line fit to $F(w)$ against w on a log-log plot as:

$$F(w) \propto w^\alpha$$

DFA is a widely enforced technique in variability analysis. It has been applied to the evaluation of posture³³, exercise³⁴, sleep stages³⁵, prediction of sepsis³⁶, classification of asthma³⁷ and COPD^{32,38,39}.

Approximate entropy (apen)

ApEn¹⁸, is a procedure necessary to assess the level of regularity and the unpredictability of changes over time-series. ApEn is the logarithmic ratio of component-wise matching sequences from the signal length, N . Other parameters include r , tolerance and m the embedding dimension. Here, we set m to 2 and r is 0.2 of the standard deviation of the data.

A minimum value of zero for ApEn would indicate a totally predictable series. ApEn is described mathematically as in the Kubios HRV[®] Analysis Manual⁴⁰. First a set of length m vectors u_j is formed

$$u_j = (RR_j, RR_{j+1}, \dots, RR_{j+m-1}), j = 1, 2, \dots, N - m + 1$$

The distance between these vectors is defined as the maximum absolute difference between the corresponding elements, hence,

$$d(u_j, u_k) = \max\{|RR_{j+n} - RR_{k+n}| \mid n = 0, \dots, m - 1\}$$

Next for each u_j the relative number of vectors u_k for which (u_j, u_k) is calculated. This index is denoted with and can be written in the form

$$C_j^m(r) = \frac{\text{nbrof}\{u_k \mid d(u_j, u_k) \leq r\}}{N - m + 1} \forall k.$$

Due to the normalisation, the value of $C_j^m(r)$ is always smaller or equal to 1. Note that the value is at least $1/(N - m + 1)$ since u_j is also included in the count. Then, take the natural logarithm of each $C_j^m(r)$ and average over j to yield.

$$\Phi^m(r) = \frac{1}{N - m + 1} \sum_{j=1}^{N-m+1} \ln C_j^m(r).$$

Finally, the ApEn is obtained as

$$\text{ApEn}(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r).$$

Sample entropy (SampEn)

SampEn^{19,40} is analogous to ApEn but there are two important differences in its calculation. For ApEn, in the calculation of the number of vectors u_k for which $(u_j, u_k), r$, also the vector u_j itself is included. This ensures that $C_j^m(r)$ is always larger than zero and the logarithm can be applied, but at the same time it makes ApEn biased. In SampEn, the self-comparison of u_j is eliminated by calculating $C_j^m(r)$ as

$$C_j^m(r) = \frac{\text{nbrof} \{u_k \mid d(u_j, u_k) \leq r\}}{N - m} \quad \forall k \neq j.$$

Now the value of $C_j^m(r)$ will be between 0 and 1. Then, the values of $C_j^m(r)$ are averaged to yield:

$$C^m(r) = \frac{1}{N - m + 1} \sum_{j=1}^{N-m+1} C_j^m(r).$$

SampEn is deduced as

$$\text{SampEn}(m, r, N) = \ln(C^m(r) / C^{m+1}(r)).$$

Again, the embedding dimension is m and the tolerance parameter r (where, $m=2$ and $r=0.2$ of the standard deviation of the data). Both ApEn and SampEn are estimates for the negative natural logarithm of the conditional probability that a data of length N , having repeated itself within a tolerance r for m points will also repeat itself for $m+1$ points.

Higuchi fractal dimension (HFD)

Higuchi²⁶ derived his procedure to measure the fractal dimension of discrete time sequences. It is regarded as the most robust of all the fractal dimension techniques and can be enforced on relatively short sections of data. It is imposed directly to the RR-intervals with no power spectrum step as is the case with the chaotic globals^{8, 9}. The phase information is maintained.

Khoa *et al*⁴¹ presented the algorithm and we adapt it below for RR intervals. It is based on a measure of length, $L(k)$, of the curve that represents the considered time-series while using a segment of k samples as a unit, if $L(k)$ scales in the following manner:

$$L(k) : k^{-Df}$$

The curve is alleged to display a fractal dimension Df . A simple curve has dimension equal to 1 and a plane has dimension equal to 2. The value of Df is always between 1 (a simple curve) and 2 (a curve which almost fills out the whole plane). Df quantifies the complexity of

the curve and so of the time-series this curve represents on a graph.

From a given time series, $RR(1), RR(2), \dots, RR(N)$, the algorithm constructs k new time series:

$$RR_{km} = \left\{ RR(m), RR(m+k), RR(m+2k), \dots, RR\left(m + \text{int}\left(\frac{(N-m)}{k}\right) \cdot k\right) \right\} \text{ for } m = 1, 2, \dots, k.$$

Where m is initial time value, k indicates the discrete time interval between points, hence the delay, k_{max} is maximum interval time, $\text{int}(a)$ is integer part of a real number a .

For each of the time-series RR_{km} constructed, the average length $L_m(k)$ is then computed as:

$$L_m(k) = \frac{1}{k} \left[\sum_{i=1}^{\text{int}\left(\frac{(N-m)}{k}\right)} |RR(m+i \cdot k) - RR(m+(i-1) \cdot k)| \right] \times \frac{N-1}{\text{int}\left(\frac{(N-m)}{k}\right) \cdot k}$$

N is total number of RR intervals. Subsequently, the length of the curve for time interval k is expressed as the sum value over k sets of $L_m(k)$ as illustrated by the following equation.

$$L(k) = \frac{1}{k} \sum_{m=1}^k L_m(k)$$

Lastly, the slope of the curve $\ln(L(k)) / \ln(1/k)$ is estimated using least squares linear best fit and the resulting slope is the HFD. To select a suitable value for k_{max} , HFD values are plotted against a range of k_{max} . The point at which the fractal dimension plateaus is considered a saturation point. That appropriate k_{max} value should be selected.

Katz's fractal dimension

Regarding the Katz's algorithm²⁷ this fractal dimension is once more calculated directly from the time-series. This algorithm has the advantage over that of Higuchi's in that a k_{max} parameter is superfluous. Yet, it has the difficulty that it requires a longer time-series to achieve significant results. Therefore we apply a cubic spline interpolation⁴² at levels 1 Hz to 15 Hz. As a consequence the number of samples in the datasets increases by 1000 per 1 Hz increase. It is important to recall that an accurate value for any type of fractal dimension should be between 1 and 2, as stated in the preceding section (see results later).

$$\text{Katz} = \frac{\text{Log}_{10}(L/a)}{\text{Log}_{10}(d/a)}$$

L is the total length of the time-series and d is the Euclidean distance between the first point in the series and the point that provides the furthest distance with respect to this first point. If we set a to be the mean distance between successive points and, n as the number of steps in the curve, then $n = L/a$.

$$\text{Katz} = \frac{\text{Log}_{10}(n)}{\text{Log}_{10}(d/L) + \text{Log}_{10}(n)}$$

RESULTS

Parametric statistics recognize that the relevant datasets are normally distributed, hence the use of the mean as a measure of central tendency. If we cannot normalize the data it is unsuitable to compare means. To authenticate normality we executed the Anderson-Darling⁴³ and Ryan-

Joiner⁴⁴ tests. Unfortunately, the results were inconclusive so we are unable to assert that the observations follow either a normal or non-normal distribution. Thus, we applied both parametric and non-parametric tests of significance. These are the One-Way Analysis of Variance (ANOVA)⁴⁵ and the Kruskal-Wallis⁴⁶ tests of significance.

To quantify the magnitude of difference between protocols for significant differences, the effect size was calculated via Cohen's d ⁴⁷. Large effect size was considered for values greater than or equal to 0.9, medium for values between 0.9 and 0.5 and small for values between 0.5 and 0.25

Table 1: The table below illustrates the mean values and standard deviation for five values of Entropy (Approximate, Sample, Shannon, Renyi and Tsallis) and Detrended Fluctuation Analysis (DFA) for the normal and youth obesity subjects (both n=43) RR-intervals. ANOVA1 and Kruskal-Wallis tests of significance calculated and the Cohen's d effect sizes were computed.

Entropy & DFA	Mean Normal	±SD Normal	Mean Youth Obese	±SD Youth Obese	ANOVA1 p-value	Kruskal-Wallis p-value	Effect Size Cohen's d
ApEn	0.8789	0.0628	0.8976	0.0815	0.2356	0.0938	0.26
SampEn	0.8646	0.0733	0.8534	0.0936	0.5355	0.6471	-0.13
DFA	0.2935	0.1818	0.3524	0.1899	0.1457	0.0781	0.32
Shannon	0.6668	0.1067	0.7709	0.1046	<0.0001	<0.0001	0.99
Renyi	0.9895	0.0039	0.9932	0.0033	<0.0001	<0.0001	1.02
Tsallis	0.6997	0.0977	0.7953	0.0941	<0.0001	<0.0001	1.00

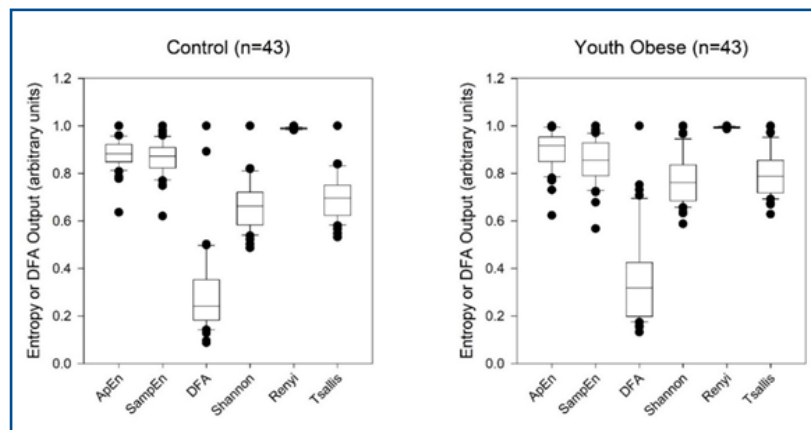


Figure 1: The boxplots of the six measures of complexity (Approximate, Sample, Shannon, Renyi and Tsallis Entropies and DFA) for control and obese youth subjects (both n=43). The point closest to the zero is the minimum and the point farthest away is the maximum. The point next closest to the zero is the 5th percentile and the point next farthest away is the 95th percentile. The boundary of the box closest to zero indicates the 25th percentile, a line within the box marks the median (not the mean), and the boundary of the box farthest from zero indicates the 75th percentile. The difference between these points is the inter-quartile range (IQR). Whiskers (or error bars) above and below the box indicate the 90th and 10th percentiles respectively.

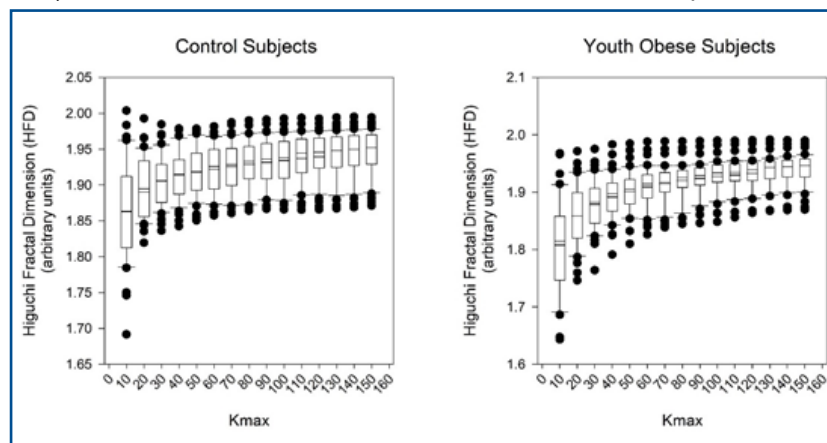


Figure 2: Box-and-whiskers plot for Higuchi fractal dimension of RR-intervals the Control subjects (left) and the obese youth subjects (right) calculated multiple times from 10 to 150 in equidistant units for different levels of K_{max} .

Table 2: HFD statistics through kmax between 10 and 150 at intervals of 10 in the normal and youth obesity subjects. The statistics include mean and standard deviation HFD for normal and youth obesity (both n=43). Their level of significance was tested by ANOVA1, Kruskal-Wallis technique and Cohen's d effect sizes.

HFD Parameter (k _{max})	Mean HFD Normal	±SD HFD Normal	Mean HFD Youth Obese	±SD HFD Youth Obese	ANOVA1 p-value	Kruskal-Wallis p-value	Effect Size Cohen's d
10	1.8628	0.0690	1.8078	0.0807	0.0010	0.0023	0.73
20	1.8946	0.0422	1.8585	0.0526	0.0007	0.0029	0.76
30	1.9062	0.0360	1.8788	0.0433	0.0020	0.0038	0.69
40	1.9139	0.0344	1.8916	0.0388	0.0061	0.0092	0.61
50	1.9187	0.0338	1.9013	0.0362	0.0235	0.0333	0.50
60	1.9220	0.0342	1.9094	0.0345	0.0912	0.0981	0.37
70	1.9256	0.0346	1.9151	0.0328	0.1525	0.1385	0.31
80	1.9288	0.0343	1.9201	0.0311	0.2191	0.1821	0.27
90	1.9318	0.0340	1.9238	0.0297	0.2487	0.1737	0.25
100	1.9343	0.0336	1.9273	0.0294	0.3052	0.2316	0.22
110	1.9369	0.0330	1.9301	0.0289	0.3120	0.2561	0.22
120	1.9395	0.0329	1.9327	0.0286	0.3092	0.2350	0.22
130	1.9415	0.0326	1.9354	0.0282	0.3557	0.2597	0.20
140	1.9434	0.0322	1.9380	0.0274	0.4009	0.2316	0.18
150	1.9450	0.0318	1.9401	0.0265	0.4390	0.1821	0.17

The results reveal extensive variation for both the non-obese controls and those from the obese youths (see Table 1 and Figure 1). The results for the Approximate Entropy, Sample Entropy and DFA are insignificant and so are not discussed further. The results for Shannon, Renyi and Tsallis entropy are all highly significant on the basis of all three statistical tests (p<0.0001 & Cohen's d ≈ 1.0 large effect size). In all three cases there is a significant increase in chaotic response.

Next, we assessed the HFD there were several

significant results at numerous levels of kmax. These values of kmax were between 10 and 50 and all achieved a p<0.05 (<5%) and a Cohen's d effect size of d > 0.5, a medium effect size. However, the algorithm performed optimally with a kmax of 20 (ANOVA1 and Cohen's d). This was related to a decrease in mean values for HFD from normal non-obese to obese youths. This was assumed to be the saturation point. During the HFD analysis exactly 1000 RR intervals from the two groups was enforced.

Table 3: The mean and standard deviations for the Katz's fractal dimension. There were equal groups of subjects for normal and youth obesity (both n=43) and the number of RR intervals in the dataset was 1000. We then enforced a cubic spline interpolation at levels 1Hz to 15 Hz. Then the number of samples in the datasets enlarged from 1000 to 15000. Levels of significance tested by ANOVA1 and Kruskal-Wallis techniques and, the Cohen's d effect sizes.

Cubic Spline Interpolation (Hz)	Mean Katz Normal	±SD Katz Normal	Mean Katz Youth Obese	±SD Katz Youth Obese	ANOVA1 p-value	Kruskal-Wallis p-value	Effect Size Cohen's d
1	2.1095	0.2364	1.9792	0.2089	0.0082	0.0195	0.58
2	1.6503	0.1327	1.5768	0.1232	0.0093	0.0229	0.57
3	1.4825	0.1012	1.4264	0.0952	0.0097	0.0218	0.57
4	1.3900	0.0852	1.3428	0.0805	0.0100	0.0234	0.57
5	1.3296	0.0752	1.2881	0.0710	0.0101	0.0229	0.57
6	1.2864	0.0682	1.2489	0.0642	0.0103	0.0218	0.57
7	1.2535	0.0628	1.2190	0.0590	0.0104	0.0218	0.57
8	1.2274	0.0586	1.1954	0.0547	0.0105	0.0229	0.56
9	1.2062	0.0550	1.1762	0.0512	0.0106	0.0234	0.56
10	1.1884	0.0520	1.1602	0.0481	0.0107	0.0234	0.56
11	1.1734	0.0494	1.1467	0.0454	0.0108	0.0239	0.56
12	1.1604	0.0471	1.1350	0.0430	0.0109	0.0239	0.56
13	1.1490	0.0450	1.1249	0.0409	0.0109	0.0245	0.56
14	1.1391	0.0432	1.1160	0.0389	0.0110	0.0245	0.56
15	1.1302	0.0414	1.1081	0.0371	0.0111	0.0250	0.56

Unlike HFD the Katz's algorithm necessitates a longer time-series. Accordingly, we enforced a cubic spline interpolation⁴² at levels 1 Hz to 15 Hz. As a consequence the number of samples in the datasets enlarged from 1000 to 15000 increasing by 1000 per single 1 Hz increase.

It should be emphasized that with a cubic spline interpolation of 1Hz (the original time-series) the results were erroneous because they gave a value of Katz's fractal dimensions greater than 2. This is inappropriate as all fractal dimensions are required to be between 1 (simple curve) and 2. (curve almost filling entire plane) This error is assumed to be attributable to the too shorter time series.

There was an optimal level of significance with a decrease in mean values from normal non-obese to youth obese for the Katz's algorithm ($p \approx 0.02$; $\approx 2\%$ both ANOVA1 & Kruskal-Wallis tests) and a medium effect size (Cohen's $d \approx 0.57$) for a cubic spline interpolation of 2 Hz. With longer time-series and cubic spline interpolations greater than 2Hz the significances of the results gradually decline for all three statistical tests.

DISCUSSION

The development of algorithms to function as statistical markers of pathological disease states is an ongoing process. This is particularly the case with the measurements based on RR-intervals by non-linear dynamics and their relationship with the "dynamical diseases." Time and frequency domain or geometric methods can incorrectly interpret the level of pathology.

Previously when employing short-time series for the assessment of chaotic response in youth obese subjects we have computed the chaotic global techniques to discriminate between control subjects and those obese youths¹⁴. Generally, these chaotic global techniques are sufficient. However, during the power spectral step through Welch or MTM, the phase information is lost. This was the motivation to apply the same data to other techniques based on nonlinear dynamics. There were five entropies, DFA and two categories of fractal dimension. Here the phase information is preserved and they are less computer processor expensive.

The responses of Approximate and Sample Entropies and DFA are insignificant. However, by applying Shannon, Renyi and Tsallis Entropies a significant increase in values for obese youths was observed, suggesting that the series of RR intervals in these individuals is less predictable. There was a slight statistical advantage for the Renyi Entropy over Shannon and Tsallis when assessed by effect size Cohen's d with the entropic order $\alpha = 0.25$. But, they were largely similar on ANOVA1 and Kruskal-Wallis statistical tests.

In a preceding study by Vanderlei *et al*⁴⁸ with obese children a similar connection was found. But, the previous study with obese children⁴⁸ found that Approximate Entropy was also significant ($p < 0.01$, $< 1\%$). Further, in this study we calculated DFA and this was also established statistically insignificant.

In relation the HFD ($p < 0.003$, $p \approx 0.3\%$; $d \approx 0.76$ medium effect size) was revealed to be superior to the Katz's fractal dimension ($p \approx 0.02$, $p \approx 2\%$; $d \approx 0.57$ medium effect size) when the ANOVA1, Kruskal-Wallis and Cohen's d tests were computed. These were both significant decreases in chaotic response by Higuchi and Katz's fractal dimension of HRV

in obese youth subjects. The decreases in chaotic response attributable to the fractal dimensions are uncharacteristic.

Some chaotic global (including CFP1, CFP3 and CFP6)¹⁴ and the Shannon, Renyi and Tsallis Entropies (see Table 1 and Figure 1 above) have been revealed to increase in magnitude for the obese youths using the identical dataset¹⁴. Besides, when applied to obese children the most robust chaotic global (CFP1; with $p \approx 0.05$;⁴⁹) and four out of five measures of entropy, not the Sample Entropy ($p > 0.05$)⁴⁸ significantly increased in obese children. Interestingly, in a study of malnourished children⁵⁰ the chaotic global parameters (CFP1 & CFP3) significantly decreased, the opposite response to obesity in children or obese youths; excluding consideration of the two fractal dimensions. It could therefore be assumed that whilst the fractal dimension techniques described here discriminate between the two cohorts of data they cannot be used effectively or reliably as a statistical marker for youth obesity. It is advisable that in this case the chaotic globals or three entropic techniques are unmatched.

The relationship between youth obesity and complexity measures such as chaotic globals and the three entropies (Shannon, Renyi and Tsallis) is beneficial in the risk assessment of diseases associated with obesity. Through non-invasive technology it identifies the level of severity from a low-cost yet reliable method of monitoring the ANS. This is helpful in treatments, such as the determination of the extent of dietary or pharmacological interventions required in the purported "dynamical diseases."

Yet, proceeding cautiously, since the subject's autonomic modulation may be critical. It should be highlighted that malnutrition by large has the opposite effect on the chaotic responses of RR-intervals to chaotic globals and entropies, excluding the two fractal dimensions; Higuchi and Katz's. Also, it should be distinguished that there are other conditions, such as diabetes mellitus and COPD which could cause similar correlations.

CONCLUSION

On the basis of three measurements of non-linearity, namely Shannon, Renyi and Tsallis Entropy young obese subjects have exhibited an increase suggesting a series of RR intervals that are less predictable. It was revealed that both Higuchi and Katz's fractal dimension can discriminate between the two groups. The Higuchi fractal dimension was optimal with a k_{max} of 20 and with 1000 samples. For the Katz's Fractal Dimension the maximal discrimination between the groups necessitated a cubic spline interpolation of 2Hz and therefore 2000 samples. Yet these fractal dimension techniques lead to a decrease in chaotic response when comparing normal non-obese to obese youths. This is atypical. So it is advisable to enforce chaotic globals or the three named entropies as a statistical marker for obesity as they are more consistent.

Competing interests

The authors declare that there is no conflict of interests regarding the publication of this article

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Abstract

Introduction: Heart rate variability (HRV) can be assessed from RR-intervals. These are derived from an electrocardiographic PQRST-signature and can deviate in a chaotic or irregular manner. In the past, techniques from statistical physics have allowed researchers to study such systems.

Objective: This study planned to assess the heart rate dynamics in young obese subjects by nonlinear metrics to heart rate variability.

Method: 86 subjects were split equally according to status. Heart rate was recorded with the subjects resting in a dorsal (prone) position for 30 minutes. The complexity of the RR-intervals was assessed by five Entropies, Detrended Fluctuation Analysis, Higuchi and Katz's fractal dimensions. Following inconclusive tests of normality we calculated the One-Way Analysis of Variance, Kruskal-Wallis, and the Effect Sizes by Cohen's d significances.

Results: It was established that Shannon, Renyi and Tsallis Entropies and the Higuchi and Katz's fractal dimensions could significantly discriminate the two groups. The three entropies were higher in obese youths, suggesting less predictable sets of RR intervals ($p < 0.0001$; $d \approx 1.0$). Whilst the Higuchi ($p < 0.003$; $d \approx 0.76$) and Katz's ($p \approx 0.02$; $d \approx 0.57$) fractal dimensions were lower in obese youths.

Conclusion: As with chaotic globals an increase in response was detected by three measures of entropy in young obese. This is counter to the decreasing response detected by fractal dimensions. Chaotic globals and entropies are more dependable than fractal dimensions when assessing the responses to obesity.

Keywords: youth obesity, detrended fluctuation analysis, entropy, fractal dimensions

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