Application of the Poincaré plot to heart rate variability: a new measure of functional status in heart failure

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Abstract
Background: Conventional methods of quantifying heart rate variability using summary statistics have shown that decreased variability is associated with increased mortality in heart failure. However, many patients with heart failure have arrhythmias which make the 'raw' heart rate variability data less suitable for the use of summary statistical measures.

Aims: To examine the clinical potential of a new measure of heart rate variability data, presented by the Poincaré plot pattern, as an adjunct to the summary statistical measures of R-R interval variability.

Methods: We used the Poincaré plot pattern to display beat-to-beat heart rate variability data from a group of 23 patients with heart failure and compared them with data collected from 20 healthy age-matched control subjects. The data, which consisted of 2000 consecutive R-R intervals, were gathered over 20-40 minutes while the subjects rested supine in a quiet darkened room.

Results: The morphological classification scheme proposed reflected the functional status of patients in heart failure. There was a significant difference (chi-square = 27.5, $df = 6$, $p < 0.0001$) in the different pattern types between patients with NYHA Class I and II compared to patients with NYHA Class III and IV. All healthy subjects displayed a 'cluster' type of pattern characterised by normally distributed data. Sixteen of the 23 patients in heart failure also produced data which were normally distributed but the remaining seven produced data which required careful filtering to make them suitable for analysis using summary statistics, but which could be analysed by the Poincaré plot.

Conclusions: The Poincaré plot pattern is a semi-quantitative tool which can be applied to the analysis of R-R interval data. It has potential advantages in that it allows assessment of data which are grossly non-Gaussian in distribution, and is a simple and easily implemented method which can be used in a clinical setting to augment the standard electrocardiogram to provide 'real time' visualisation of data. (Aust NZ J Med 1995; 25: 18-26.)
Key words: Poincaré plot, heart rate variability, heart failure.

INTRODUCTION

Sympathetic-parasympathetic interactions have been well studied and their importance established in a number of cardiovascular diseases. These include heart failure[1] in which increased sympathetic and decreased parasympathetic activity is common.[2,3] Various methods have been used to attempt to quantify these autonomic influences.[4] Recently, there has been considerable interest in the study of heart rate variability as one such approach and a number of indices have been used to quantitate this.[5] A recent study has shown that variations in the shape of R-R interval histograms taken from data gathered over a 24 hour period correspond to different New York Heart Association

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(NYHA) functional classes and that clinical progression of disease may be associated with further reductions in heart rate variability.[6]

The study of heart rate variability using the standard deviation and derived indices as a measure of variance assumes that data are normally distributed. Not only may this be inappropriate and invalid in a significant percentage of studies, but this method is extremely sensitive to artefact and ectopic activity which occur frequently in patients with heart failure.

The purpose of this project was to assess the value of the Poincaré plot as a new technique for quantifying heart rate variability data gathered over a relatively short time in patients with heart failure. The Poincaré plot is a scatterplot of current R-R interval against the immediately following R-R interval.[7,8] It allows a more instantaneous measure of interbeat interval than indices gathered over a longer time span, usually from Holter monitoring. It can be used to display heart rate variability information in a compact visual format which is readily interpreted in a qualitative and semi-quantitative manner. Theoretically it might complement other standard procedures for the analysis of heart rate variability such as statistical (time domain) measures, the tachogram, histogram and frequency domain (power spectral density) analysis.[9]

METHODS

Subjects

Patients were recruited from a general practitioner clinic and included in the study after they had given informed consent. They were classified on clinical grounds into the following two age-matched groups.

Group 1. Healthy subjects ($n = 20$, 8 M/12 F, aged 60-81 years, mean 71.4 years, SD 5.0 years). Subjects were clinically healthy, normotensive, had a normal electrocardiogram and were on no cardiovascular drugs.

Group 2. Patients with cardiac failure ($n = 23$, 12 M/19 F, aged 56-85 years, mean 75.2 years, SD 6.5 years).

A total of 23 patients with systolic heart failure were assessed clinically and categorised into four groups according to the NYHA classification system as shown in Table 1. Echocardiograms were performed on all patients and showed impaired left ventricular systolic function. The underlying pathological basis was coronary heart disease in 18, idiopathic dilated cardiomyopathy in two, and aortic and/or mitral valve disease in three. Study data were collected while patients continued their usual treatment for heart failure, an accepted limitation.

TABLE 1
Group 2: Patients with Heart Failure

Group 2. Heart failure	NYHA class	Number of patients
$n = 23$	I	4
Age 75.4 ± 6.7 years	II	11
(Mean ± SD)	III	3
	IV	5
	Total	23

Abbreviations: SD = standard deviation; NYHA = New York Heart Association.

Recording Technique

Patients were instructed to avoid caffeinated beverages and cigarettes for three hours before the study and were rested supine on a couch in a quiet darkened room for ten minutes prior to data collection. All subjects were in sinus rhythm and were examined in the postabsorptive state between 10.00 am and 3.00 pm. They were instructed to relax and breathe quietly for the duration of the study. A total of 2000 data points were collected and used to generate the Poincaré plot. Accordingly, data epochs varied from 20 to 40 minutes.

The electrocardiograms were processed by an interpretive ECG machine (Burdick Elite) and results checked by a cardiologist. The analogue output port of the ECG machine was used to transmit a raw signal to a computerised QRS detector which was custom-built for the purpose of the study (full details are given in the appendix) and calibrated on a digital and analogue pulse generator to an accuracy of ± 1 ms.

Standard statistical methods for the analysis of heart rate variability were used, including the plotting of R-R interval tachograms and the respective R-R and delta R-R histograms and standard deviations.[10]

For frequency domain indices, the application of spectral analysis to heart rate variability remains problematic because of unresolved questions relating to the optimal size of the data set, non-stationarity, the type of algorithm which is optimal and the presence of ectopic activity.[11] This study focused exclusively on conventional (time domain) statistics because they have been widely applied and are being implemented in some commercial systems allowing automated analysis of the electrocardiogram.

In all cases data were interpreted blinded to clinical details.

Filtering Technique

Artefact and occasional ectopic beats occurred in almost all heart rate variability studies. To reduce the effect of such 'noise', filters can be used to remove selected portions of the R-R interval data (time series). A conventional technique filters the R-R time series by replacing ectopic beats with an interpolative splined R-R interval. This technique is effective in removing the most obvious ectopic beats from the data but may not remove all 'outlying' points. We used the Poincaré plot to check the adequacy of this conventional filtering technique which is applied to the raw R-R

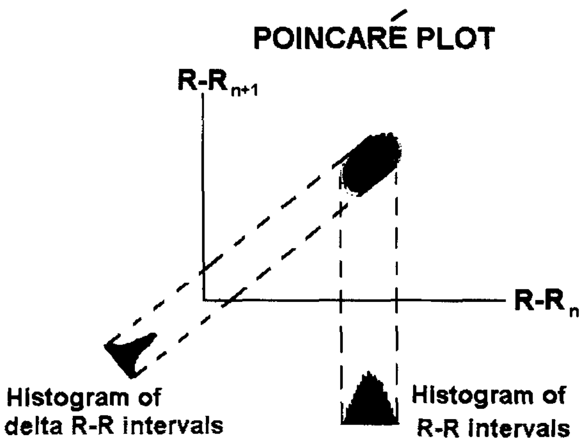


Figure 1: The Poincaré plot pattern is a scatter plot of cardiac R-R intervals (R-R_{n+1}) against the previous intervals (R-R_n) and can be quantified by measuring the standard deviation of the R-R and delta R-R intervals. The R-R interval histogram relates to the projection of the plot on to the x axis whereas the delta R-R interval histogram relates to the dispersion of points around the line of identity.

interval data until the filtered Poincaré plot represents as close as possible the original Poincaré plot with all the outlying data points removed.

Technical Aspects of Poincaré Patterns

The Poincaré or Lorenz plot is a scatterplot of current R-R interval against the R-R interval immediately preceding it. In mathematical terminology, this device is termed a 'return map' and is used extensively in the physical sciences to analyse dynamical processes. This simple construction provides summary information as well as information about the instantaneous beat-to-beat behaviour of the heart. When the basic rhythm is very regular with little interbeat variability, points representing the R-R interval are spread closely along the line of identity, the diagonal line at an angle of 45 degrees to both axes. Any points below this indicate a shorter R-R interval relative to the preceding R-R interval. Similarly, any points above the diagonal line indicate an R-R interval longer than the preceding R-R interval.[8]

Consequent to this it becomes apparent that the degree of heart rate variability is graphically displayed as a pattern of points which lends itself to analysis more readily than simple summary statistical measures such as the standard deviation of R-R intervals applied to normally distributed data. It also provides a visual display of both the overall and beat-to-beat variability.[12] Histograms of R-R and delta R-R data associated with the Poincaré plot can be quantified by the analysis of variance of the respective data. The standard deviation of the R-R interval histogram relates to the variance of the data distributed along the diagonal line of the Poincaré plot projected on to the x axis. The standard deviation of the difference between R-R intervals (delta R-R) relates to the variance of the distribution of data points perpendicular to the diagonal line. It may be an indicator of rapid heart rate fluctuations due to the modulation of vagal tone.[13] These aspects of the Poincaré plot are illustrated in Figure 1. This allows the classification of the various Poincaré plot patterns to be based on objective measures of variance, and normality or otherwise of data distribution.

Statistical Methods

The categorisation of data into normal or non-normal frequency distributions was based on the examination of R-R and delta R-R interval histograms[6,14] and normal probability plots. Non-normal data was characterised by marked skewness or multimodal distribution. Heart rate variability data histograms were accepted as stationary if the mean and variance of R-R intervals remained constant throughout the study. Non-parametric Chi-square statistics were used to compare the frequency of occurrence of different Poincaré plot patterns between the normal subjects and those with cardiac failure. Non-parametric, between groups analysis (Kruskal-Wallis ANOVA) was used to assess the significance of conventional measures of heart rate variability between groups.

RESULTS

Classification of Poincaré Patterns

The nomenclature used in this article is adapted from that proposed by Woo *et al.*,[7] with some modifications due to the differing methods of data collection. The Poincaré patterns were classified into four broad groups based on the pattern of distribution of R-R and delta R-R intervals and the ratio of variance (or SD) of R-R to delta R-R intervals which we have defined as the aspect ratio.

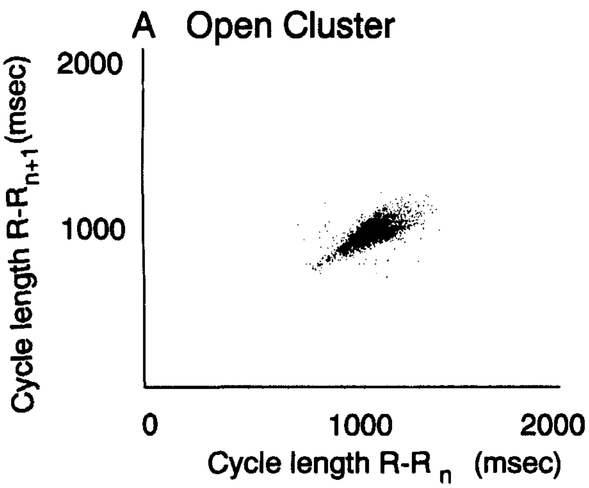
The four broad groups were:

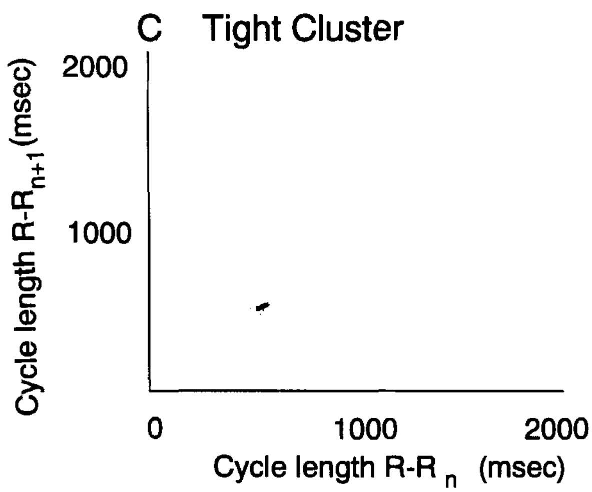
- 'Cluster patterns'; normally distributed data
- 'Elongated patterns: cigar shapes'; elongated normally distributed data
- 'Complex and fan-shaped patterns'; non-normally distributed data
- 'Comet shapes'; non-stationary data.

Patterns of heart rate variability in subjects in Group 1 (healthy subjects)

All subjects in this group shared a characteristic pattern in their Poincaré plot. They displayed a Gaussian (normal) clustering of points which we termed a 'cluster' pattern, characterised by the SD of R-R intervals of 20-80 ms and of delta R-R intervals >10 ms, with an aspect ratio of <2.2.

The typical Poincaré plot pattern found in the healthy subjects in our group was therefore markedly different to that produced by the healthy subjects in the study by Woo *et al.*, who described a 'comet' pattern from heart rate variability data gathered over 24 hours.





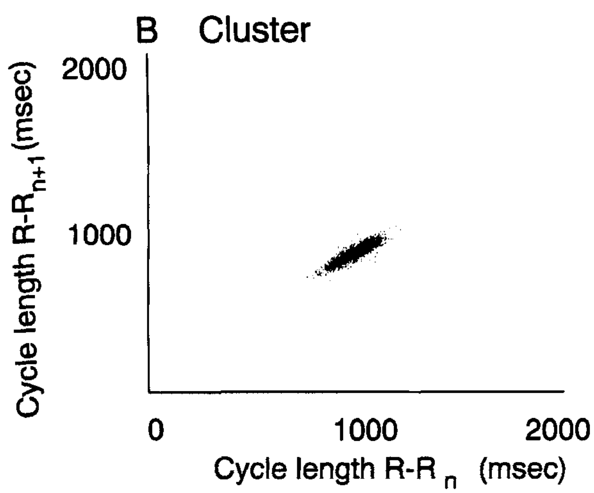


Figure 2: Gaussian R-R data distribution: Cluster Poincaré plot pattern types – *Panel A* is an 'open cluster' pattern; the standard deviation of R-R and delta R-R intervals was 87 and 64 msec, respectively. This pattern was seen in a 68-year-old female patient with heart failure in NYHA Class II being treated with captopril. *Panel B* is a 'cluster' pattern from a 65-year-old healthy female. This was the dominant pattern seen in healthy subjects. The standard deviation of R-R and delta R-R interval was 56 and 29 msec, respectively. *Panel C* is a 'tight cluster' pattern; the standard deviation of R-R and delta R-R intervals was 11 and 6 msec, respectively. This pattern was seen from a 72-year-old female patient with heart failure secondary to ischaemic heart disease and on treatment with frusemide.

Poincaré patterns observed in Group 2: Patients with cardiac failure

Cluster type patterns were seen in 13 of the patients with heart failure (57%). Such clusters were subdivided into three major groups based on the standard deviation of the R-R and delta R-R intervals, and on the aspect ratio. In the remaining ten patients we characterised other patterns of the Poincaré plot using the statistical parameters already discussed. The various patterns are described.

1. Normally distributed data: 'cluster types' (illustrated in Figure 2)

'Open cluster': data with SD of R-R intervals >80 ms.
'Cluster': pattern characterised by SD of R-R intervals of 20-80 ms and SD of delta R-R intervals >10 ms, with an aspect ratio of <2.2.
'Tight cluster': data with SD of R-R intervals <20 ms.

2. Elongated patterns with normal distribution of data (illustrated in Figure 3; panels A and B)

Cigar patterns were characterised by an elongated Poincaré plot pattern with an aspect ratio >2.2. This group was classified into two sub-groups based on the SD of delta R-R intervals.
'Fat cigar': defined as data with SD of R-R intervals of 20-80 ms and SD of delta R-R intervals of >10 ms with the aspect ratio >2.2.
'Cigar': SD of R-R intervals of 20-80 ms, SD of delta R-R intervals <10 ms, and aspect ratio >2.2.

3. Non-stationary data (illustrated in Figure 3; panel C)

The 'comet' pattern was defined by Woo *et al.*,[7] as the pattern is reminiscent of a comet because of its narrow 'head' and broad 'tail'. In our study, this pattern was produced by data considered to be non-stationary, although the pattern was defined as being the norm by Woo *et al.*[7] This may have been due to method-

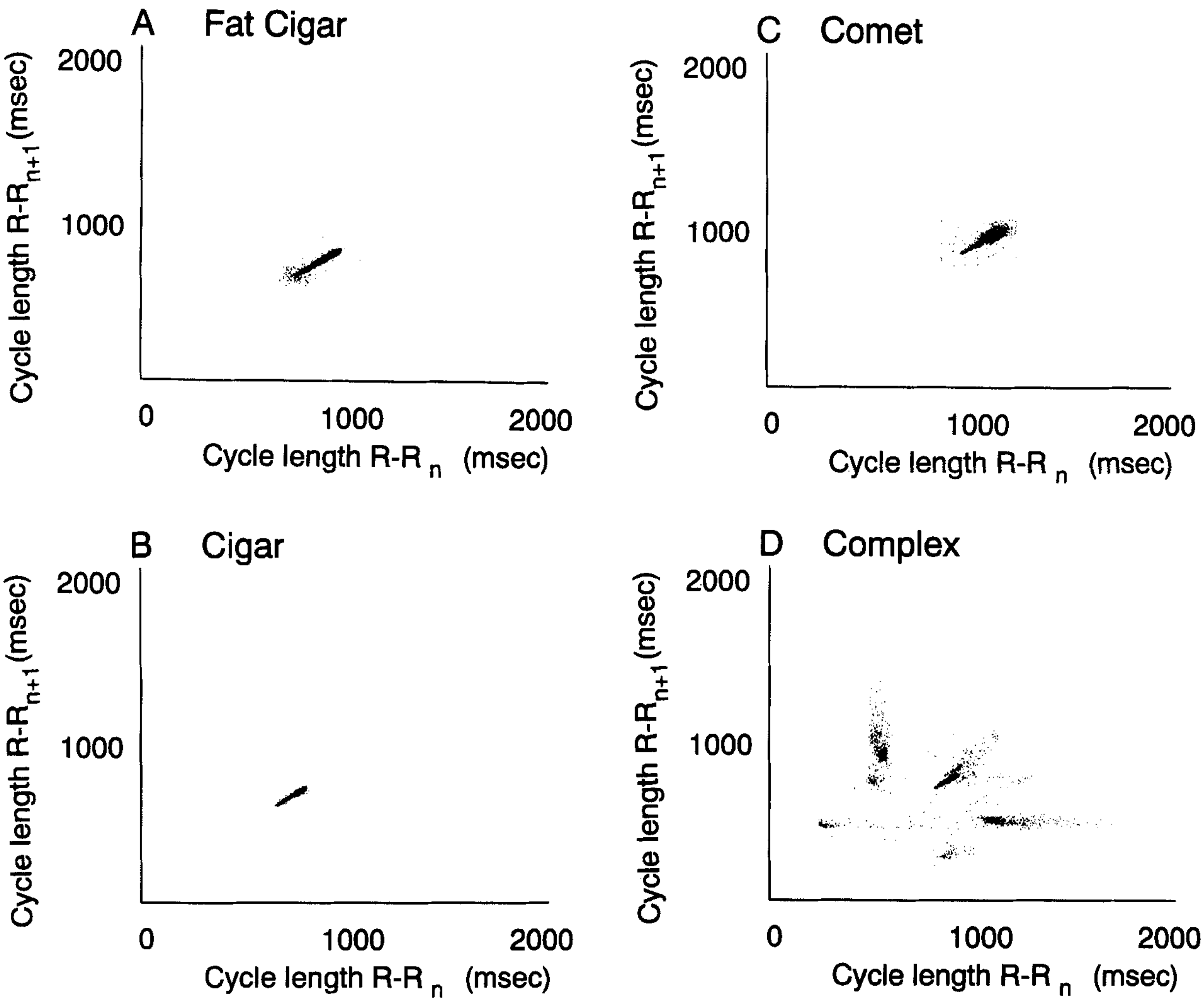


Figure 3: Elongated and non-Gaussian Poincaré plot pattern types: Elongated Poincaré plot pattern types – *Panel A* is a 'fat cigar'; the standard deviation of R-R and delta R-R intervals was 50 and 16 msec, respectively. This plot was from a 78-year-old male in NYHA Class I being treated with captopril. *Panel B* is a 'cigar' or 'torpedo'; the standard deviation of R-R and delta R-R intervals was 30 and 7 msec, respectively. This plot was from a 65-year-old female patient in NYHA Class II, taking digoxin and frusemide. Non-stationary R-R interval data – *Panel C* is a 'comet' shape due to non-stationarity of data from a 78-year-old female in NYHA Class IV. Her heart failure was secondary to severe aortic stenosis and moderate mitral regurgitation. She was being treated with frusemide and enalapril. Grossly non-Gaussian R-R interval data – *Panel D* is a 'complex' pattern with a central 'cluster' and several satellite clusters due to ventricular ectopic activity in a 56-year-old female with heart failure in NYHA Class IV being treated with frusemide and captopril.

ological differences in data collection, as these investigators employed prolonged ambulatory monitoring of the electrocardiogram, rather than data collected over a shorter period at rest as we have done. The narrow 'head' of the 'comet' pattern, reflecting decreased variability, may have been due to increased sympathetic tone associated with physical activity and the broad 'tail' at longer R-R intervals due to increased variability at rest associated with an increase in parasympathetic tone. Stationarity of data implies that the mean and variance of the time series is constant throughout. Non-stationarity of data may thereby invalidate the statistical measures which are used to characterise the patterns.

4. Non-normal data (illustrated in Figure 3; panel D) 'Complex' pattern characterised by a 'central cluster' of data with satellite clusters resulting from ectopic activity and the corresponding 'echo' generated as a natural artefact in the plot, due in many instances to a post-ectopic pause. Satellite points appear as additional mini-clusters grouped around the main 'cluster'.[15]

Poincaré plot patterns from the cohort of patients with heart failure are shown in Table 2.

Non-parametric Chi-square statistics confirmed that the difference in patterns between Group 1 (normal) and Group 2 (cardiac failure) patients was highly significant (Chi-square = 22, df = 6, $p < 0.001$). Due to the

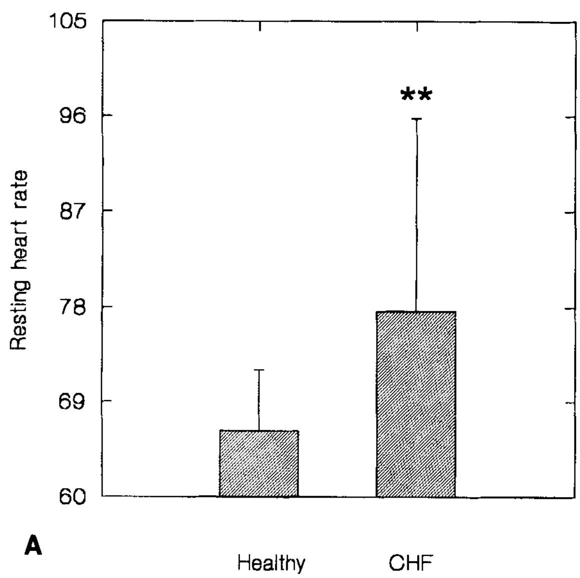
TABLE 2
Poincaré Plot Patterns in Heart Failure Patients Grouped by NYHA Class

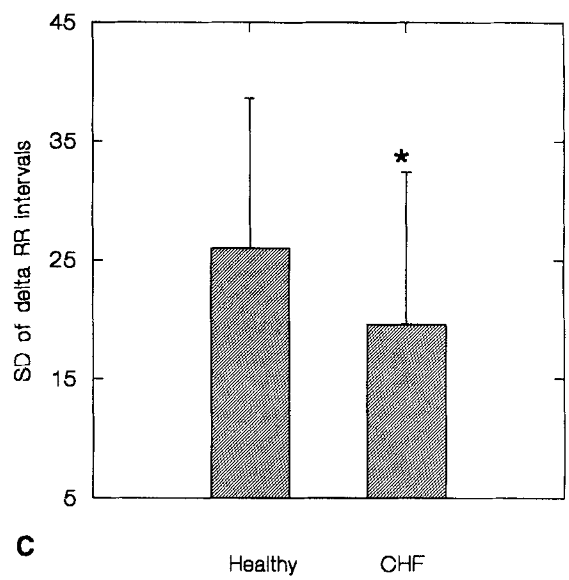
Pattern	NYHA I	NYHA II	NYHA III	NYHA IV
Open cluster	0	1	0	0
Cluster	3	6	0	0
Tight cluster	0	2	1	0
Fat cigar	1	0	0	0
Cigar	0	1	0	1
Comet	0	0	0	1
Complex	0	1	2	3
Total	4	11	3	5

Abbreviations: NYHA = New York Heart Association.

small number of patients in the study we were unable to show that the difference in pattern types between individual NYHA Classes was statistically significant. However, when we compared the pattern types between patients with NYHA Class I and II to patients with NYHA Class III and IV, the Chi-square test confirmed the statistical significance (Chi-square = 27.5, df = 6, $p < 0.0001$).

Of the conventional time domain measures applied to carefully filtered data, the resting heart rate ($p < 0.01$), SD of R-R ($p < 0.001$) and delta R-R ($p < 0.05$) intervals discriminated between healthy subjects and all patients with heart failure as illustrated





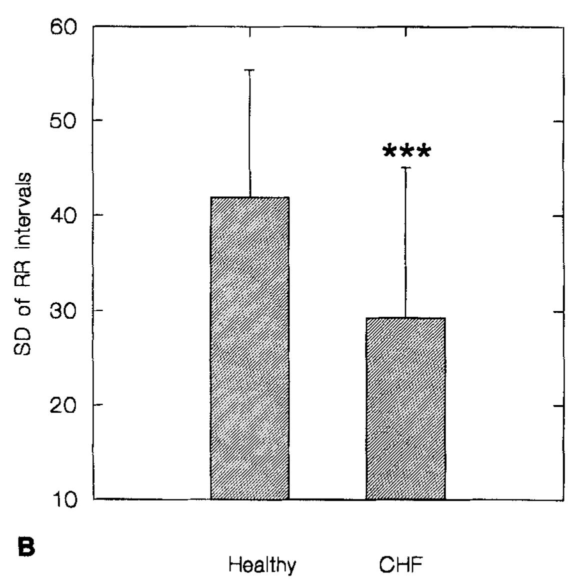


Figure 4: Conventional time domain measures of heart rate variability between the healthy subjects (HS) and patients with chronic heart failure (CHF). *(a)* Resting heart rate (HS 66.3 ± 5.8 bpm; CHF 73.4 ± 13.9 bpm; $p < 0.01$). *(b)* SD of R-R intervals (HS 41.9 ± 13.5 msec; CHF 29.7 ± 16.0 msec; $p < 0.001$). *(c)* SD of delta R-R intervals (HS 26.0 ± 12.6 msec; CHF 20.3 ± 13.2 msec; $p < 0.05$). *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

in Figure 4. When heart failure patients were grouped into NYHA Class I and II and NYHA Class III and IV the heart rate ($p<0.05$) and SD of R-R intervals ($p<0.05$) discriminated between the heart failure patients and the healthy subjects. However, when we compared the healthy subjects to the patients in heart failure in their respective NYHA Classes there was no significant difference between the groups. Our small sample size may have contributed to the lack of statistical significance although we cannot rule out the possibility that there may not be a difference in the heart rate variability parameters between the heart failure patients. There were insufficient numbers to demonstrate a difference in conventional measures of heart rate variability between patients with heart failure with different NYHA Classes.

DISCUSSION

This study demonstrates that the Poincaré plots of R-R intervals reveal distinctive patterns that distinguish healthy subjects from patients in heart failure. It is postulated that the Poincaré plot pattern reflects the different patterns of autonomic activity of patients with heart failure. Heart failure patients have sympathetic overactivity,[16,17] reduced parasympathetic activity[18] and depressed baroreceptor responsiveness.[19] In fact, high sympathetic activity is a potent descriptor of poor survival,[20] whereas high vagal tone provides some degree of cardioprotection.[21]

There are several invasive techniques which can provide some measure of autonomic function. These include microneurographic measurements of sympathetic nervous activity[22] and regional catecholamine 'spillover'[23] which has been used to reflect sympathetic activity in particular organs such as the heart. However, there are as yet no reliable non-invasive tests available to allow complete assessment of autonomic function.[24]

Assessment of variability in the rate of discharge of the sinus node is a logical approach to measurement of activity of the autonomic nervous system.[25] It is generally accepted that reflex activation of cardiac autonomic efferents and consequent change in heart rate involves a reciprocal balance of excitatory sympathetic influences counteracted by the inhibitory effects of the cardiac parasympathetic nervous system.[26] Of these, vagal influences are generally more rapidly acting and of relatively greater magnitude in the healthy heart.[27,28] Heart rate variability has long been recognised to be a sign of cardiac health and a reduction in variability has been associated with a poor prognosis in patients following acute myocardial infarction.[29,30] Until recently, heart rate variability has usually been assessed by analysis of R-R intervals with the use of measurements in the time domain, including standard deviation, and spectral techniques (use of fast Fourier transform and autoregressive algorithms) to enable analysis in the frequency domain.[4]

However, these methods may not necessarily be ideal. The interactions between the sympathetic and parasympathetic nervous systems which influence the automaticity of the sinus node[31] and result in heart rate variability are complex.[32,33] This complex behaviour may be due to an equally complex process or it may be caused by a number of relatively simple but nonlinear mechanisms such as neurohormonal and mechanical influences.[34]

The use of the Poincaré plot may provide a tool with which to probe these complex interactions which linear tools such as summary statistics and spectral analysis fail to achieve fully.[35-37] An additional concern with the more traditional techniques is the requirement to filter data which have been 'corrupted' by ectopic or arrhythmic events. In contrast, the Poincaré plot can be used to display the entire unfiltered data set to allow careful inspection of data for any patterns which may otherwise go unrecognised. Furthermore, the Poincaré plot can also be used to assess the adequacy of a filtering process both in terms of completeness and to detect introduced artefact.

Summary statistical measures and frequency domain measures such as power spectral analysis are adversely affected by outlying data points unless the raw data are carefully filtered. The method of Camm,[38] applying a 'triangular index' to the R-R interval data (and delta R-R), is an alternative to filtering and can be readily applied to the Poincaré plot pattern. However, this method can only be accurately applied to data which have a uni-modal distribution pattern and are not markedly skewed. We found that the qualitative assessment of the Poincaré plot pattern proved resistant to the influence of ectopic beats and other arrhythmias and provided a two dimensional perspective of heart rate variability data.

Bigger *et al.*,[39] have shown a very strong correlation between power in the high frequency energy of the normal R-R interval power spectrum and the root mean squared successive difference (r-MSSD) of normal R-R intervals. We confirmed that the standard deviation of the successive differences between R-R intervals[40] and r-MSSD are equivalent to the delta R-R interval measure which we have used to quantify the short axis of the Poincaré plot. Therefore the Poincaré plot pattern displays the interaction between the R-R interval and delta R-R interval data. We are not aware of any prior report demonstrating this relationship.

It is worthy of further comment that in contrast to most (but not all[41]) studies in heart rate variability which rely on data collected during prolonged ambulatory Holter monitoring, our patients were resting quietly with data collected over a relatively short time-frame of 20-40 minutes. This was the likely explanation for the fact that our healthy subjects did not display Poincaré plot patterns with the characteristic 'comet' and 'stem' shape seen in the patterns of healthy subjects in the study of Woo *et al.*,[7] who employed 24 hour ambulatory monitoring. The small 'head' of their 'comet' pattern was probably the result of increased sympathetic activity resulting in an increase in absolute heart rate and associated reduction in heart rate variability.

These disparate findings in normal subjects contrast to the patterns of the Poincaré plots produced by the patients with heart failure in our study, in whom the results were in close agreement with Woo *et al.*[7] In this regard it is possible that discrepancies arising from the use of variable recording techniques may be less when there is relative sympathetic overactivity at rest as occurs in patients with heart failure. This contrasts to the normal situation at rest when vagal influences predominate.

Finally, although unproven, the 'complex' patterns in our data could have resulted, at least partly, from arrhythmic/ectopic activity and the corresponding 'echoes' from the post-ectopic pause resulting in additional mini-clusters grouped around the main 'cluster'. This could explain the particular observation of this pattern in patients with severe heart failure.[15] However, ventricular arrhythmias would be less likely to be the explanation for the other patterns seen in our heart failure patients.

Potential Applications

We have shown that Poincaré plot patterns obtained from heart rate variability data collected over a relatively short time frame can provide useful information which may not otherwise be readily available. The close correlation between the pattern type and the functional status of heart failure patients may make the method a potentially useful tool for further classifying patients. The Poincaré plot may also provide an accurate means of assessing the value of various drug interventions in such patients.[42,43]

With the improvement over recent years in management of cardiovascular diseases in which autonomic influences are important, the accurate stratification of patients into high and low risk groups is becoming increasingly important. The study of heart rate variability may provide a cheap, relatively rapid and non-invasive method to meet this challenge. ■

Acknowledgements

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Appendix

Technical Details of the Electronic Data Processing Equipment

The raw ECG 1 volt signal was buffered by a unity gain operational amplifier and then differentiated with an appropriate time constant to maximise the R wave. The signal was then rectified to provide a positive going peak which triggered a threshold and fired a 300 s monostable. The output of the monostable went to the optoisolator.

Counting was performed by cascaded 4040 and 4024 ripple counters, whose output was latched into 74374 tristate D flipflops. The count was held there until interrogated from the computer in 4 bit parcels via a 74257 multiplexer and the parallel port. A master 4 MHz quartz clock, divided down to provide a signal for the counters, sent a 4001 flipflop flag to the waiting computer. This process took place in less than 10 μs seconds after the 4017 had been enabled by a pulse from the optoisolator. Counting then recommenced until the next pulse. The equipment was calibrated on a digital and analogue pulse generator and R-R intervals were measured to an accuracy of ± 1 ms of Poincaré plot patterns.

Poincaré plots were plotted from raw, unfiltered data. An IBM PC 486 was used to process the data using custom written software to calculate the Poincaré plot, tachogram, histogram and power spectrum.

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