A New Heart Rate Variability Analysis Method by Means of Quantifying the Variation of Nonlinear Dynamic Patterns

Hang Ding*, Stuart Crozier, and Stephen Wilson

Abstract—A new heart rate variability (HRV) analysis method, quantifying the variation of nonlinear dynamic pattern (VNDP) in heart rate series, is proposed and validated against the age stratified Fantasia database. The method is based on three processes: 1) a recurrence quantification analysis (RQA) to quantify the dynamic patterns, 2) the use of mutual information (MI) and the entropy (EN) to characterize the VNDP, and 3) linear discriminant analysis to exploit the associations within MI and EN measures. Practically, the VNDP method overcomes the nonstationarity problem and exploits the nonstationary properties in HRV analyses. Physiologically, the VNDP reflects the properties of the fundamental short-term HRV dynamic system and the external associations of the system within the autonomous nervous system (ANS). The characteristic probability density peaks portrayed by VNDP plots indicate the quantum-like heart dynamics, which may provide valuable insights into the control of the ANS. The discrimination results of the reduced pattern dynamic range due to aging, from a new perspective, display the reduction in HRV. The significantly improved discriminatory power, compared to conventional RQA analyses, shows that the VNDP analysis can practically quantify the nonstationary nonlinear dynamics for ANS assessments.

Index Terms—Entropy (EN), heart rate variability (HRV), mutual information (MI), recurrence quantification analysis (RQA), variation of nonlinear dynamic pattern (VNDP).

I. INTRODUCTION

The analysis of heart rate variability (HRV), the variation of period between consecutive heart beats, provides valuable information to assess the autonomous nervous system (ANS), which can be significantly affected by many disease states and physiological changes. HRV analysis is becoming a major new diagnostic tool. Its low cost, noninvasive nature, and effectiveness encourage the development of new HRV analysis methods to broaden and improve its applications.

One principle difficulty with the analysis of the HRV is that heart rate dynamics are nonlinear [1]–[3] and nonstationary [4]–[6]. Traditional HRV analysis methods are based on linear methods in the time or frequency domain to reveal the fundamental control activities of sympathetic division (SYD) and parasympathetic division (PYD) within the ANS [7]. These methods have limited power to discriminate nonlinear dynamics. Classical nonlinear analysis methods, such as Lyapunov exponent [8], fractal dimensions [9], Poincare plots [10], and correlation analysis [11], etc., are based on long stationary dynamic data series. Although these nonlinear analysis methods are successfully applied to provide some insights about the heart rate control system, nonstationary heart rate dynamics, in practice, can significantly degrade these nonlinear analysis results. Mathematically, nonstationarity is caused by the evolution of the control states of a dynamic system [12]. Although nonstationary nonlinear heart rate dynamics are very complex and exhibit significant fractal properties [1], [9], a fundamental nonlinear dynamic system generating explicit short-term heart rate dynamics can still be outlined within ANS. Generally, the short-term nonlinear dynamics are generated from the ion channels [13] and neural impulses [14], [15] controlled by SYD and PYD [16], [17], which are mainly modulated by the respiratory activities and arterial pressure fluctuations within ANS [18]. The SYD and PYD produce antagonistic heart rate control effects, respectively increasing and decreasing heart rate. In the HRV frequency domain, the SYD activities are mainly represented by low-frequency components (0.04–0.15 Hz, LF) and the PYD activities mainly by the high-frequency components (0.15–0.4 Hz, HF) [7]. Based on the outlined heart rate regulation mechanism, the nonstationarity can be seen as the result of the changes of control state of the fundamental nonlinear dynamic system. The control state changes may caused by the equilibrium regulatory activities of ANS, which reflect the ANS continuously responding to stimuli from its internal and external environments, such as body temperature, blood gases, anxiety, etc, to optimize the functions of organism and coordination of these functions [19], [20]. The classical nonlinear HRV analysis methods, by assuming stationary dynamics, provide overall assessments, where the characteristic nonlinear properties, in practice, are “blurred” by the ubiquitous nonstationarity. Additionally, as the characteristics of nonstationarity itself reflect the complex equilibrium control activities within ANS, they may contain valuable information for ANS assessment.

Motivated by finding a way to overcome the nonstationarity problem and to exploit the characteristic nonstationarity to improve the HRV discriminant analysis, a new HRV analysis method called variation of nonlinear dynamic patterns...
A. Recurrence Plot and RQA Measures

RQA characterizes the dynamic properties by quantifying the structures in a recurrence plot (RP), which is based on the analysis of the trajectories under an appropriate reconstruction of the dynamics [37]–[39]. The reconstruction method used in the recurrence plot is a time delay-embedding method. If the experimental data series are \( \{d(1), d(2), d(3), d(4), \ldots, d(M)\} \), the RP can be expressed as

\[
R(i,j) = \Theta(\varepsilon - ||Y(i) - Y(j)||) \tag{1}
\]

where \( || \) is the symbol of norm. In our study, the Euclidean norm is applied. \( \Theta \) is the operator of the Heaviside function. \( \varepsilon \) is the Euclidean threshold (ET). \( Y \) is the phase space vector. The two components in the delay-embedding construction in phase space are \( Y(i) \) and \( Y(j) \), which can be mathematically expressed as

\[
Y(i) = \{d(i), d(i + \tau), \ldots, d(i + (dE - 1) \cdot \tau)\} \tag{2}
\]

\[
Y(j) = \{d(j), d(j + \tau), \ldots, d(j + (dE - 1) \cdot \tau)\} \tag{3}
\]

where \( i, j = 1, 2, 3, \ldots, N \); \( dE \) is the embedding dimension; and \( \tau \) is the time delay. The recurrence plot is a \( N \times N \) binary array, where \( N = M - (dE - 1) \cdot \tau \). If the Euclidean distance between \( Y(i) \) and \( Y(j) \) falls in the threshold \( \varepsilon \), \( R(i,j) \) is 1. If the distance is further than \( \varepsilon \), \( R(i,j) \) is 0. The \( N \times N \) binary array is finally marked with the white (0) and black (1).

Three typical RQA output variables are used in this approach. Recurrence rate (REC) measures the density of the recurrence points by counting the black dots in the RP, when \( \varepsilon \) is given

\[
\text{REC} = \frac{1}{N \times N} \sum_{i,j=1}^{N} R(i,j). \tag{4}
\]

The diagonal lines in a RP represent the dynamics repeating themselves in the phase space. Determinism (DET) is defined as the percentage of the recurrent points that form upward diagonal line segments

\[
\text{DET} = \frac{\sum_{s=S_{\text{min}}}^{S} Ps(s)}{\sum_{i,j=1}^{N} R(i,j)} \tag{5}
\]

where \( Ps(s) \) is the number of the diagonal lines with the length of \( s \) in the RP and \( S_{\text{min}} \) is the minimum length of the diagonal line counted for the DET value.

Laminarity (LAM) is the percentage of the recurrent points that form vertical or horizontal line segments, which represent a relatively “quiet” dynamics (Laminar state) in the experimental series. It is mathematically expressed as

\[
\text{LAM} = \frac{\sum_{u=1}^{u_{\text{max}}} u \times Pu(u)}{\sum_{i,j=1}^{N} R(i,j)} \tag{6}
\]
Where \( \text{Pu}(\eta) \) is the number of the vertical lines with the length of \( \eta \) and \( U_{\text{min}} \) is the minimum length of the vertical line counted for the LAM value.

### B. REC Based RQA Technique Final Stage

During our RQA evaluation tests, we found that the variations of dynamic distributions and dynamic amplitudes can dramatically influence the RQA output measures and that there is not a universally accepted, standardized setup. In this paper, the REC is used to setup the RQA, as a \( \varepsilon \) value can be inversely calculated from a given REC value. The REC can be expressed as a function of the \( \varepsilon \) and an input data series \( X \), if the other RQA setup parameters are kept constant. It can be simply formulated as

\[
\text{REC} = f_{\text{REC}}(\varepsilon, X),
\]

Due to the monotonic relation between REC and \( \varepsilon \), if a REC value is given, a corresponding \( \varepsilon \) solution within an acceptable tolerance can be approximately calculated out by using bisection method. Therefore, the \( \varepsilon \) value can be expressed as a function of REC

\[
\varepsilon = f_{\text{REC}}^{-1}(\text{REC}, X),
\]

Furthermore, the DET and LAM can be expressed as

\[
\text{DET} = f_{\text{DET}}(\varepsilon, X)
\]

\[
\text{LAM} = f_{\text{LAM}}(\varepsilon, X).
\]

If we substitute the \( \varepsilon \) with \( f_{\text{REC}}^{-1}(\text{REC}, X) \), we get

\[
\text{DET} = f_{\text{DET}}(f_{\text{REC}}^{-1}(\text{REC}, X), X)
\]

\[
\text{LAM} = f_{\text{LAM}}(f_{\text{REC}}^{-1}(\text{REC}, X), X)
\]

which can be further simplified as

\[
\text{DET} = F_{\text{DET}}(\text{REC}, X)
\]

\[
\text{LAM} = F_{\text{LAM}}(\text{REC}, X).
\]

From the upper definition, it can be seen that the \( \varepsilon \) value calculated out by a given REC value represents a dynamic range in which the specifically defined recurrences fall. Since this range is determined by the intrinsic dynamic properties, it provides valuable data for the dynamic analysis. In this method, the Euclidean threshold \( \varepsilon \) determined by a given REC is newly defined as ET and used as an output variable.

This REC setup strategy provides a constant information level (a given recurrence rate) for the analysis of the other RQA output variables. The intrinsic dynamic distribution and amplitude properties can also be reflected and studied by the ET analysis. In total, three windowed RQA output variables: DET, LAM and ET are used as input for the mutual information and entropy analysis.

RQA setup: In this paper, the embedding dimension and delay time are set at 2 and 1, respectively. The choice of low embedding and unit delay for heart rate dynamics can help maintain the laminar states (vertical and horizontal structures in RP) and extract short recurrences (diagonal structures in RP) [22]. The setup value for the REC is 10%. The controlled error for the bisection method compute corresponding ET values is of \( \pm 0.05\% \). A significant recurrence value is required to obtain enough information and a relatively high REC can reduce the noise influence [14], [39]. Especially for short segment RQA discriminant analysis, the choice of relatively high REC (10%) and low embedding dimension (\( d_{\text{E}} = 2 \)) can generally result in a better discrimination power than that of low REC (REC = 1%) and high embedding dimension (\( d_{\text{E}} = 6 \) or 10) [40]. The minimum line lengths counting for DET and LAM RQA is set at \( S_{\text{min}} = U_{\text{min}} = 3 \). The length of diagonal lines represents the duration of a dynamic system recurs to a state in the phase space. However, the diagonal lines are not uniquely generated by chaotic systems. Even white noise can cause a rather large number of short diagonal lines [41]. The minimum line lengths of 3 set for DET and LAM can effectively reduce the noise influence, as the recurrences generated by noise decay greatly while increasing the minimum line length value [41]. The RQA window size is experimentally set at 90 heart rate dynamics, which contain around 3.6–13.6 components of SYP activities and 13.5–36 components of PDY activities. (60 beats/min; 90 beats in 90 s; 90 s \( \times 0.04 \text{ Hz} = 3.6 \); 90 s \( \times 0.15 \text{ Hz} = 14.5 \); \( \times 0.4 \text{ Hz} = 36 \)).

### C. Mutual Information and Entropy

Mutual information measures the dependency of two RQA variables; entropy measures the complexity. These two measures quantify high order statistics.

If \( x \) denotes the measurement of a system \( X \), and \( p_{x}(x) \) denotes the probability of \( x \), the average amount of information calculated from the measurement \( x \) is the entropy \( H \) of the system \( X \), and this is defined as [42]

\[
H(X) = - \int p_{x}(x) \log[p_{x}(x)] \, dx.
\]

According to Shannon’s information theory, if the log is taken to the base two and \( H \) is in units of bits, the probabilities of variable measurements fall in \( 2^{B} \) equally sized bins and \( H(X) \) ranges from 0 to B.

For a general coupled system \( (X, Y) \), with measurement \( x_{1}, x_{2}, x_{3}, \ldots, x_{n} \) and \( y_{1}, y_{2}, y_{3}, \ldots, y_{n} \), the mutual information \( I(X, Y) \) measures how dependent the values of \( x \) are on the values of \( y \). According to the chain rule, \( I(X, Y) \) is expressed as

\[
I(X, Y) = H(X) + H(Y) - H(X, Y) = I(Y, X)
\]

where \( H(X) \) and \( H(Y) \) are marginal entropies of \( X \) and \( Y \), respectively, and \( H(X, Y) \) is the entropy of the joint probability and is defined as

\[
H(X, Y) = - \int p_{x,y}(x,y) \log[p_{x,y}(x,y)] \, dx \, dy
\]

where \( p_{x,y}(x,y) \) is the joint probability of \( (x, y) \). The mutual information also satisfies \( I(X, Y) = I(Y, X) \), and is zero, if and only if \( X \) and \( Y \) are completely independent. The lower the entropy value, the lower the complexity.

In this paper, two selective RQA output variables are input as \( X \) and \( Y \). The mutual information of the two variables (MI)
and the entropy of the joint probability of the two variables (EN) are used to quantify the VNDP. They respectively represent the dependency of two nonlinear dynamic properties and the complexity of nonlinear dynamic patterns. The bin size is \(1/(512 \cdot 512)\); therefore, the MI and EN values range from 0 to 18.

A key process in the MI and EN application is to estimate the PDF from limited sampling points. Here, the PDFs of the DET, LAM, and ET are estimated by the product of the standard Parzen type method with Gaussian kernels [43]. An advantage of this method is that it can provide relatively accurate result even if the experimental data are sparse in certain area. Additionally, it is a consistent estimator. When the number of experimental data grows and the standard deviation decreases, the estimated conditional probability approaches the true value [43]. The disadvantage is that computation times dramatically increase, when the number of experimental data increases. If \((\text{Det}_1, \text{Lam}_1), (\text{Det}_2, \text{Lam}_2), (\text{Det}_3, \text{Lam}_3), \ldots, (\text{Det}_n, \text{Lam}_n)\) are the independent and random paired measures, the PDF of the DET and LAM \(p_{\text{DE}}(\text{Det}, \text{Lam})\) is then formulated as

\[
p_{\text{DE}}(\text{Det}, \text{Lam}) = \left\{ \left( \pi \cdot h_{\text{DET}} \right)^{-1} \sum_{k=1}^{n} K \left[ (\text{Det}_k - \text{Det}_i) / h_{\text{DET}} \right] \right\} \cdot \left\{ \left( \pi \cdot h_{\text{LAM}} \right)^{-1} \sum_{k=1}^{n} K \left[ (\text{Lam}_k - \text{Lam}_i) / h_{\text{LAM}} \right] \right\}
\]  

(18)

where \(h\) is the window width parameter, and \(K(y)\) is called a weighting function, or window function, it must satisfy

\[
|K(y)| < \infty \text{ for } -\infty < y < \infty
\]  

(19)

\[
\int |K(y)| \, dy < \infty
\]  

(20)

and

\[
\int K(y) \, dy = 1.
\]  

(21)

Parzen showed that the estimated probability density converges to the true density [43], if

\[
\lim_{n \to \infty} h(n) = 0
\]  

(22)

and

\[
\lim_{n \to \infty} nh^{d}(n) = \infty.
\]  

(23)

In this paper, we use one of Parzen proposed weighting functions

\[
K(y) = (2\pi)^{-1/2} \cdot \exp[-y^2/2].
\]  

(24)

The choice of the window width parameter \(h(n)\) is based on assuming the PDF to be approximately normal with standard deviation estimated by \(\sigma_e\), and the optimal \(h\) is calculated by [44]

\[
h = \sigma_e \cdot \left[ 8 \cdot \pi^{1/2} \cdot \int K(x)^2 \, dx \right]^{1/5}.
\]  

(25)

D. Linear Discriminant Analysis (LDA)

The fundamental LDA process is based on finding a linear composite of RQA output variables with the aim of maximizing their between-group variation relative to their within-group variation on the composite. If vector \(X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]\) denotes ith subset measures of n RQA variables, and \(W = [w_1, w_2, \ldots, w_n]\) denotes a set of weights, the composite \(u_i\) can be expressed as

\[
u_i = X_i^T \cdot W
\]  

(26)

where \(X_i^T\) is the transpose of \(X_i\). \(W\) is then optimized with the intent of maximizing the ratio

\[
\lambda = \frac{SS_A(u_i)}{SS_W(u_i)}
\]  

(27)

where \(SS_A\) and \(SS_W\) denote the among-group and within-group sums of squares of the linear composite \(u_i\). The maximum value \(\lambda\) is determined by the characteristic function [45]

\[
|B^T \cdot A - \lambda I| = 0
\]  

(28)

where A and B denote among group and within group sums of squares and cross products (SSCP) matrices, respectively.

Finally, the eigenvector with the maximum Eigenvalue \(\lambda\) from the characteristic equation (28) is used as the weight set \(W\) to develop the linear composite \(u_i\).

E. Data Flow and Evaluation of the VNDP Analysis

The data flow with the VNDP analysis consists of following stages (Fig. 1).

1) 2000 segments with a preset length (92 RR intervals) are randomly extracted from a long-term heart rate series. Totally, there are 40 data series from 20 young subjects (labeled as Y01, Y02, \ldots, Y20) and the class of 20 old subjects (labeled as Z01, Z02, \ldots, Z20).

2) Each segment is input into a RQA process to get a set of two of the three RQA output variables, are measured by the MI and EN. Totally six VNDP measures: MI(DET,LAM), MI(DET,ET), MI(LAM,ET), EN(DET, LAM), EN(LAM, ET), and EN(DET, ET) are generated.

3) The linear discriminant analysis is applied to the six VNDP measures.

4) The composite values from the corresponding subjects are plotted and statistically analyzed.

5) The 2-D PDFs of two RQA measures are estimated by the Parzen PDF estimation method.

F. Data Sources for the Evaluation

The Fantasia database from the PhysioBank [19] is organized to study the heart rate dynamic properties due to aging. In the database, there are totally forty 120 min ECG recordings respectively from 20 young subjects (21–34 years old) and 20 el-
elderly subjects (68–85 years old). These subjects are rigorously screened healthy subjects. Each group of subjects includes equal numbers of men and women. While acquiring the ECG, all subjects remained in a resting supine position in sinus rhythm and watched the movie Fantasia (Disney, 1940) to help maintain wakefulness. The continuous ECG was digitized at 250 Hz. Each heart beat was annotated using an automated arrhythmia detection algorithm and each beat annotation was verified by visual inspection [19]. Basically, the data collection experiments were structured to minimize the influence of gender, health conditions, environment and psychological factors. Based on the same database, aging related disruption in the fractal-like long-range correlations was reported [32].

III. RESULTS

The VNDP plot can portray the characteristic properties of fundamental short-term HRV dynamic system and the control state changes, reflecting external associations of the system within the ANS. The 2-D PDF of DET and LAM from an old subject (f1o01) forms a characteristic contour [Fig. 2(A)] different from that of a young subject (f1y01) [Fig. 2(C)]. In this case, it can be seen that the old subject exhibits a diagonal ridge-like region with three high-density centers and where the dynamic patterns often stay. For the young subject, the dynamic patterns are mainly focused on one center and the contour demonstrates less diagonal orientation than the old subject. The diagonal PDF orientation reflects the dependency between the two RQA variables, which, in this approach, is measured by the mutual information. If the DET is statistically independent to the LAM, the mutual information value results in zero. The dynamic pattern concentration reflects the complexity of the dynamic patterns, which is measured by the entropy. A loose PDF concentration, representing a wide range of dynamic pattern variation, results in a high entropy value [Fig. 3(a)].

The VNDP measures (MI and EN values) and their correlations contain the intrinsic and characteristic properties the heart rate control mechanism. The multivariate discrimination analysis implemented by the LDA can exploit these correlations to improve the discriminatory power. The discrimination of the young and old groups can be seen from the MI and EN scatter plots [Fig. 3(a)–(c)]. Some discriminations can be easily found from the scatter plots of individual VNDP measures, such as, the high entropy trends in young subjects derived from LAM-ET [Fig. 3(b)] and DET-ET [Fig. 3(c)]. These trends clearly indicate the reduced dynamic pattern variation in old subjects. Some discriminations are not reflected by individual VNDP measures, as the measures from MI and EN may be correlated. This correlation can be exploited by the LDA to improve the discriminatory power. For example, the young and old classes cannot be significantly separated by using individual the MI(LAM,DET) and EN(LAM,DET) measures derived from the PDF of DET and LAM [Fig. 3(a)]; however, the LDA processed results exhibits a clear separation of the two classes (Fig. 4). Compared with standardized means and corresponding standard deviations of the MI(LAM,DET) and EN(LAM,DET) measures derived from the PDF of DET and LAM [Fig. 3(a)]; however, the LDA processed results exhibits a clear separation of the two classes (Fig. 4). Compared with standardized means and corresponding standard deviations of the MI(LAM,DET), EN(LAM,DET) and LDA transformed results from two measures (Fig. 5), the LDA significantly improves the discriminatory power. When all the six variables are applied to the LDA, the scatter plot in Fig. 6 and the equalized mean and STD of the final VNDP analysis value in Fig. 5 show the significantly improved discrimination power.

Compared with the conventional RQA results (Fig. 7), the VNDP analysis results in the smallest standard deviation when the mean values are equalized. Among the conventional RQA variables, the LAM results in the best separation of the two groups. Its standard deviations are 1.25 for the old group and 0.72 for the young group. The corresponding STD values from VNDP are 0.27 and 0.37, which are only 22% and 51% of those from the LAM. This clearly demonstrates that, in this case, the VNDP analysis method provides a much better discrimination power than the conventional RQA does.
IV. DISCUSSION

The VNDP analysis provides unique characterization of the heart rate regulation by the ANS. Differing from other nonlinear HRV analysis methods focusing only one nonlinear property, this method, by integrating nonlinear RQA method, reliable information analysis techniques and general LDA, analyzes the heart rate dynamics from the aspects of both nonlinearity and nonstationarity. The VNDP plot can uniquely portray the HRV nonstationary properties of the nonlinear heart rate regulation system. Although some control state changes may be abrupt and can induce certain nonstationarity in the temporally windowed segments, the abrupt nonstationarity does not significantly induce biases as the windowed power spectrum analysis does, because the nonstationary properties can still be seen as dynamic transient patterns, which reflect the control state characteristics. In the VNDP plots, the PDF clearly displays nonGaussian distribution profile. Some PDF plots exhibit characteristic multi high density distribution peaks. These peaks interestingly indicate that the existence of the quantum-like heart rate regulation particularly in large scales, which dynamic regulation processes are limited within certain discrete states and tend to shift from state to state. This finding implies that the underlying variation of the control states, causing nonstationarity, may be governed or limited to a number of control mechanisms, or feedback loops, and the control activities may be migrating between

![Fig. 3](image1)
![Fig. 4](image2)
![Fig. 5](image3)
![Fig. 6](image4)
these mechanisms. The implied discrete control states is consistent with the ANS regulatory structure, which involves some major nonlinear processes of the self-organization mechanisms and some major process loops within the central regulation governed by the brain stem [19]. In conventional RQA analysis, these characteristic VNDP profiles normally are simply “averaged” and the “averaging” process generally degrades the quantification of the real nonlinear recurrence properties.

With respect to the VNDP application to the Fantasia database, the results confirm the reduced HRV due to aging process and indicate the correlated variation in ANS control network. For normal healthy young subjects under rest condition, their heart rate regulation systems generally exhibit dynamical, flexible and adaptive characteristics. Correspondingly the heart rate displays complex dynamics. Although the knowledge on how the aging process causes ANS changes is incomplete, generally and significantly reduced HRV due to aging has been reported [36]. In this study, the result of significantly reduced entropy values of the ET related VNDP plots in the aging group show the reduced nonlinear pattern in terms of dynamic range (unstable period orbits), which indicates the decreased dynamic amplitude due to reduced senescence on cardiac dynamics (or simply reduced sensitivity) in aging [35] and which is also consistent with the reduced multifractality (detrended analysis) [31], [32] and the reduced dynamic entropy [36] in heart rate dynamics due to aging. The difference on the EN values and MI values on DET and LAM between the two study groups is not significant. However, a significant correlation between the two VNDP measures can be found. This correlation indicates that, in the aging process, some control mechanisms are maintained, but their associations within the ANS are shifted. The association among VNDP measures may arise from the underlying dynamic expression of the control of the cardiovascular system and its complex interactions within an ANS. Although those MI and EN measures may not be linearly associated, the information underlying the associations can be simply exploited by using the linear discriminant analysis method.

V. CONCLUSION

This VNDP analysis method provides a new way to study the HRV. Mathematically it overcomes the nonstationary interference on the quantification of nonlinear properties in heart rate dynamic series. Physiologically it reflects the properties of fundamental short-term HRV dynamic regulation system and its external associations within the ANS control network. With respect to the VNDP application to the Fantasia database, the results display the reduced pattern dynamic range due to aging and the associations within the VNDP measures. Compared with the conventional RQA method, the significant improved discrimination power clearly shows that the VNDP method can well represent and quantify the characteristic of the heart rate dynamics to reflect the underlying control mechanism. The implications from the multi control state centers on VNDP plots and the associations of VNDP measurements provides valuable information to understand and study the heart rate dynamic regulation mechanism.

REFERENCES


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