33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Analysis of degree of nonlinearity and stochastic nature of HRV signal during meditation using delay vector variance method

L. Ram Gopal Reddy, Srinivas Kuntamalla

Abstract—**Heart rate variability analysis is fast gaining acceptance as a potential non-invasive means of autonomic nervous system assessment in research as well as clinical domains. In this study, a new nonlinear analysis method is used to detect the degree of nonlinearity and stochastic nature of heart rate variability signals during two forms of meditation (Chi and Kundalini). The data obtained from an online and widely used public database (i.e., MIT/BIH physionet database), is used in this study. The method used is the delay vector variance (DVV) method, which is a unified method for detecting the presence of determinism and nonlinearity in a time series and is based upon the examination of local predictability of a signal. From the results it is clear that there is a significant change in the nonlinearity and stochastic nature of the signal before and during the meditation (p value > 0.01). During Chi meditation there is a increase in stochastic nature and decrease in nonlinear nature of the signal. There is a significant decrease in the degree of nonlinearity and stochastic nature during Kundalini meditation.**

Index Terms: **meditation, nonlinearity, stochastic nature, heart rate variability, delay vector variance**

I. Introduction

Heart rate variability (HRV) analysis is gaining acceptance as a potential non-invasive means of assessment of autonomic nervous system in research and clinical domains. Heart rate dynamics is nonlinear in nature and it is proved that nonlinear analysis of HRV provides more appropriate information for understanding and interpretation of the physiological problems associated with cardiovascular system [1].

Meditation is a complex physiological process which affects neural, psychological, behavioral, and autonomic functions, and is considered as an altered state of consciousness, differing from wakefulness, relaxation at rest, and sleep. Many meditation traditions consider breath, body and mind are linked, and thus have given the breath a central role in meditation practice. Slower respiration rate during meditation practice induces changes in the cardiovascular activity that corresponds to an increase in the activity of restorative parasympathetic system [2]. This increased parasympathetic activity has also been assessed through the slowing down of basal heart rate in meditators, and the increased synchronization, or respiratory sinus arrhythmia (RSA), between the breathing cycle and the heart beat during meditation [3].

In this paper, the HRV data obtained before and during the Chi and Kundalini meditation is analyzed for its nonlinearity and stochastic nature using the method of delay vector variance. The delay vector variance (DVV) is a unified method for detecting the presence of determinism and nonlinearity in a time series and is based upon the examination of local predictability of a signal [4], [5].

II. Methods

A. Data group

A publicly available RR inter beat interval database (www.physionet.org) consisting of data before and during meditation, collected from eight healthy Qigong meditation (Chi meditation) subjects (aged 29-35) and four Kundalini yoga meditators, 2 women and 2 men (aged 20-52) is utilized (more information on the dataset and the meditation method are described in [6]). The length of the time series varied between 50 and 80 minutes. One characteristic case of the RR interval time series, before and during meditation, is presented in Figure 1, in which the evident irregular character of the time series before meditation transcends to smoother cyclic oscillations during meditation.

B. Surrogate Data Generation

A surrogate signal is a realization of null hypothesis, which in this context is that the original time series is linear. Iterative Amplitude Adjusted Fourier Transform (IAAFT) approach described in [7] is used to generate surrogates for this study because it yields superior results and overcomes the normal distribution problem of phase randomization method [8] , [9]. This approach retains the amplitude spectrum and distribution of the original signal.

C. Delay Vector Variance method

A time series can be represented in phase space conveniently using time delay embedding. When time delay is embedded into a time series it can be represented by a set of delay vectors (DVs) of a given dimension. If m is the dimension of the delay vectors then it can be expressed as X (k) =[$x_{(k-m\tau)}$ ……. $x_{(k-\tau)}$], where τ is the time lag. Now for every DV X (k), there is a corresponding target, namely the next sample x_k. A set β_k (m, d) is generated by grouping those DVs that are within a certain Euclidean distance (d) to

L. Ram Gopal Reddy is a Professor of Physics, National Institute of Technology, Warangal, INDIA (lrgreddy@gmail.com)

Srinivas kuntamalla is a Research Scholar in Physics Department, National Institute of Technology, Warangal, INDIA (ksvchary@gmail.com)

978-1-4244-4122-8/11/$26.00 ©2011 IEEE

DV X(k).This Euclidean distance will be varied in a manner standardized with respect to the distribution of pair wise distances between DVs. Now for a given embedding dimension m, a measure of unpredictability σ^{*2} (target variance) is computed over all sets of β_k. The variation of the standardized distance enables the complete range of pair wise distances to be examined. The procedure for Delay Vector Variance method can be summarized as below [4], [5].

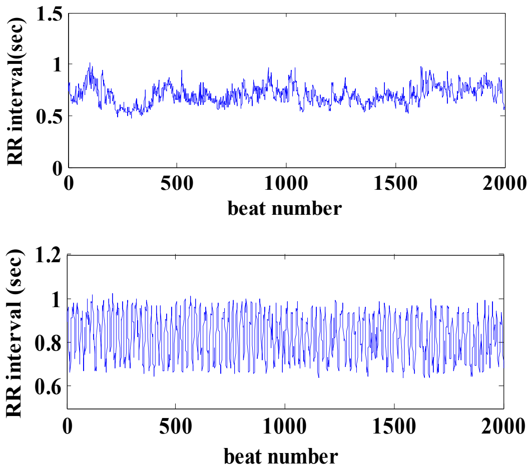

Fig. 1. RR intervals before (top plot) and during meditation (bottom plot)

The mean μ_d and the standard deviation σ_d are computed over all pair wise Euclidean distances between DVs given by $\|x(i) - x(j)\|$ $(i \neq j)$. The sets β_k (m, d) are generated such that $\beta_k = \{x(i) | \|x(k) - x(i)\| \leq d\}$ i.e. , sets which consist of all DVs that lie closer to X(k) than a certain distance d, taken from the interval [μ_d -n_d σ_d ; μ_d +n_d σ_d] where n_d is a parameter controlling the span over which to perform DVV analysis. For every set β_k (m, d) the variance of the corresponding targets $\sigma_k^2(m, d)$ is computed. The average over all sets β_k (m, d) is divided by the variance of the time series signal , σ_k gives the inverse measure of predictability, namely target variance $\sigma^{*2}(m, d)$. The variance is computed only if there are at least 30 DVs in a set β_k (m, d).

The plot of target variance $\sigma^{*2}(m, d)$ as a function of spans d for a given dimension m is called DVV plot and as the distance is standardized it is easy to interpret the plot. At the extreme right, the DVV plots smoothly converges to unity, since for maximum spans, all DVs belong to the same universal set, and the variance of the targets is equal to the variance of the time series.

DVV scatter diagrams are produced using the original time series and its surrogates. If the surrogate signals yield DVV plots similar to that of the original time series, the 'DVV scatter diagram' coincides with the bisector line and original signal is linear. If the surrogate time series yield DVV plots not similar to that of the original time series, the curve will deviate from the bisector line and original time series is non-linear. Thus the deviation from the bisector line is an indication of nonlinearity, and can be quantified as root mean square error (RMS error) between the σ^{*2} s of the original time series and the σ^{*2} s averaged over the DVV plots of the surrogate data.

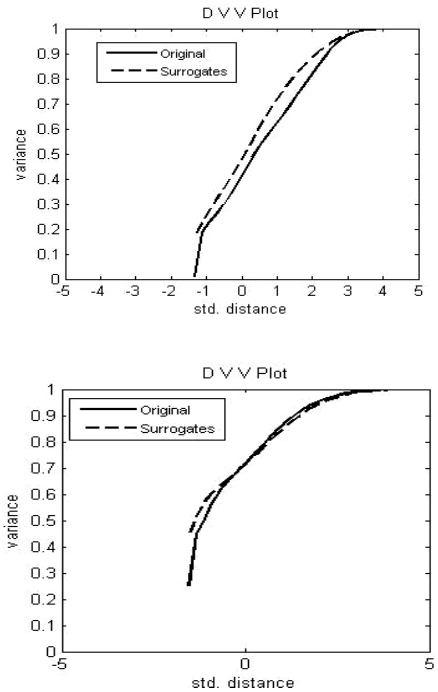

Fig. 2. DVV plots (top plot - before meditation, bottom plot – during meditation) for a subject (c7) in chi meditation group (solid curve) and average DVV plots computed over 25 surrogates (dashed curve)

In this paper, optimum time delay embedding dimension is considered as to ensure a common dimension for all the subjects for comparison. Therefore, all the parameters are computed for given dimension (m=5) and given distance parameter (n_d=5) and τ =1. Twenty five surrogates are generated using IAAFT method. As reported by Temujin Gautama et al. [5], the length of the time series must be greater than 1000, otherwise there is a profound effect on minimum target variance. The length of time series considered in this paper is 2000 samples. The feature extraction and implementation of method is done in Matlab 7.3.

III. RESULTS

The parameters extracted from DVV plots and DVV Scatter diagrams are tested for null hypothesis using a significance test (T-test). T-test is the most commonly used method to evaluate the differences in means between the two groups. The significance level for rejection of null hypothesis is set to 0.01 in this study. The p value < 0.01 is considered to be statistically significant.

The value of minimum target variance for a Chi meditator (c7) is 0.0116 before meditation and 0.2595 during meditation (Fig. 2.). The minimum target variance, $\sigma^{*2}_{min}(m)$ is a measure of noise present in the time series.

The amount of noise is indicative of the stochastic component prevalent. The presence of strong deterministic component will lead to small target variance for small spans. This shows that Chi meditation increases stochastic nature of HRV. From Fig. 3., the value of RMS error of a Chi meditator (c7) is 0.0609 before meditation and 0.0384 during meditation. Thus there is an increased linearity during Chi meditation.

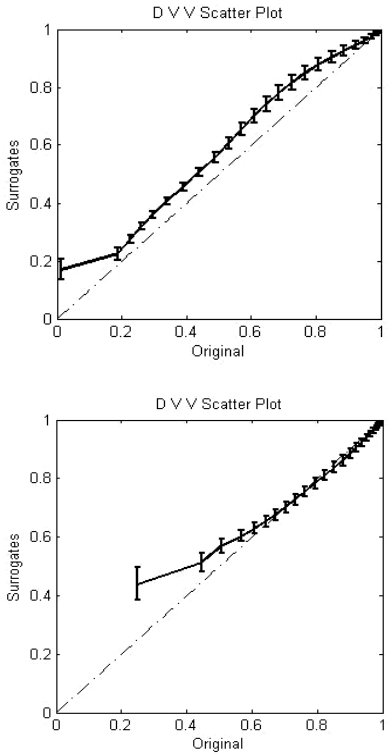

Fig. 3. DVV Scatter plots (top plot- before meditation, bottom plot – during meditation) for a subject (c7) in chi meditation group

The value of minimum target variance for a Kundalini meditator (y2) is 0.2107 before meditation and 0.0349 during meditation (Fig. 4). The stochastic component of HRV is therefore, significantly reduced during Kundalini meditation. DVV Scatter plots (top plot - before meditation, bottom plot – during meditation) for a subject (y2) in Kundalini meditation group are shown in Figure 5. The value of RMS error is 0.0614 before meditation and 0.0144 during meditation. Kundalini yoga seems to greatly increase the linearity of HRV signal. Figures 6 and 7 show Box – Whiskers plot for the parameters determined from DVV plots and DVV scatter diagrams for Chi and Kundalini meditation groups.

IV. CONCLUSION

The average value of minimum target variance for Chi meditation is 0.0918(±0.0518) before meditation and 0.1708(±0.0421) during meditation (p value > 0.01). The average value of RMS error for Chi meditation is 0.0227(±0.0207) before meditation and 0.011(±0.0095) during meditation (p value > 0.01). The average value of minimum target variance for Kundalini yoga is 0.0658(±0.0313) during meditation and 0.3139(±0.0961) before meditation (p value > 0.01). The average value of RMS error for Kundalini meditation is 0.0242(±0.0143) during meditation and 0.0607(±0.0298) before meditation (p value > 0.01).

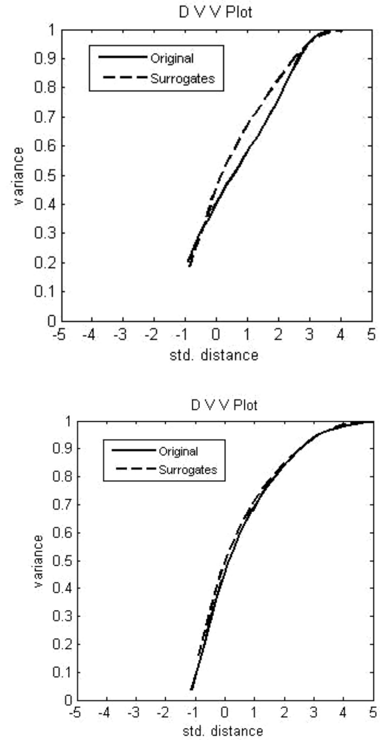

Fig. 4. DVV plots (top plot- during meditation, bottom plot – before meditation) for a subject (y2) in kundalini meditation group (solid curve) and average DVV plots computed over 25 surrogates (dashed curve)

From the plots and results, it is clear that there is a significant change in the nonlinearity and stochastic nature of the signal before and during the meditation (p value > 0.01). There is a decrease in the degree of nonlinearity during the two forms of meditation while the determinism is increased in Kundalini yoga and decreased in Chi meditation. These changes are may be because of state of induced deep mental relaxation, which brings about the changes in the cardiovascular system function. It is proved by many investigators that meditation brings about greater coordination and harmony between the mind and body [2]. With increased inward attention during meditation there is more withdrawal of the body and mind from external senses which yields control to the vagal innervation. The significant decrease observed in the nonlinearity of HRV signal during the two forms of meditation should probably be a reflection of this i.e., the underlying mechanism responsible for HRV is relatively simpler during meditation. During the Kundalini meditation the nonlinearity and stochastic nature of HRV are markedly decreased, while the nonlinearity is decreased and the stochastic nature of HRV is increased during chi meditation. The increase in stochasticity is note worthy. This might have probably arised owing to the difference in the processes adopted in Chi and Kundalini meditation. While chi meditation employs visualization technique, mantras are chanted in Kundalini yoga.

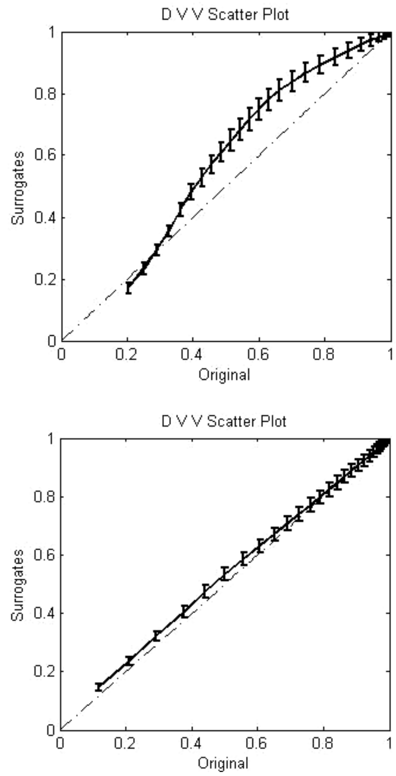

Fig. 5. DVV Scatter plots (top plot- before meditation, bottom plot – during meditation) for a subject (y2) in kundalini meditation group

ACKNOWLEDGMENT

The authors are thankful to Danilo P. Mandec et al. for providing the DVV toolbox for Matlab under GNU general public license.

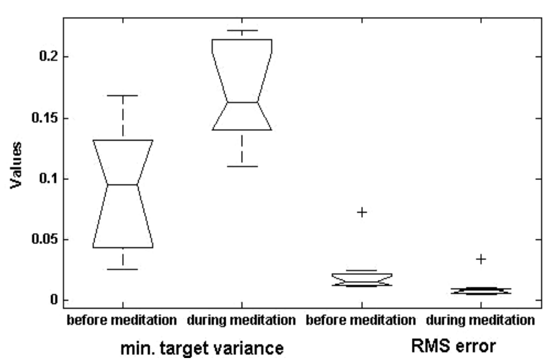

Fig. 6. Box – Whiskers plot for the parameters determined from DVV plots and DVV scatter plots for Chi meditation group.

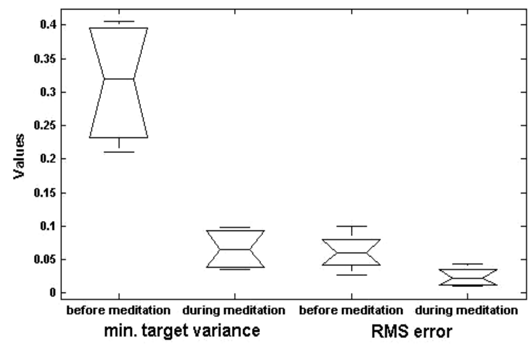

Fig. 7. Box – Whiskers plot for the parameters determined from DVV plots and DVV scatter plots for kundalini meditation group.

REFERENCES

[1] C. Karmakar, *et al.*, "Defining asymmetry in heart rate variability signals using a Poincaré plot," *Physiological measurement,* vol. 30, 2009.

[2] Shr-Da Wu and Pei_Chen Lo, "Inward-attention meditation increases parasympathetic activity: a study based on heart rate variability", *Biomedical Research,* 29(5), pp 245-250, 2008.

[3] B.S. Raghavendra and D. Narayan Dutt, " Nonlinear Dynamical characterization of heart rate variability time series of meditation", *International journal of biological and life sciences,* vol 8 no. 3 , pp167-177, 2012.

[4] Temujin Gautama, Danilo P. Mandic , Marc M. Van Hulle, "The delay vector variance method for detecting determinism and nonlinearity in time series", *Physica D*, 190, pp 167–176, 2004.

[5] Temujin Gautama, Danilo P. Mandic , Marc M. Van Hulle, "A Novel method for determining the nature of time series", *IEEE trans. Biomed. Engg*., vol. 51, no. 5, pp 728-736, 2004.

[6] C-K Peng et al, " Exaggerated heart rate oscillations during two meditation techniques", *International journal of cardiology,* vol 70, pp 101-107, 1999.

[7] T. Schreiber and A. Schmitz, "Improved surrogate data for nonlinearity tests", *Phys.Rev. Lett*., 77, pp 635-638,1996.

[8] T. Schreiber and A. Schmitz, "Surrogate time series", *Physica D*, vol. 142, no.3-4, pp346-382, 2000.

[9] Theiler, S. Eubank, A. Longtin, B. Galdrikian and J.D. Farmer, "Testing for nonlinearity in time series: The method of surrogate data", *Physica D*, 58, pp 77-94, 1992.