Cardiovascular and Cardiorespiratory Signals Complexity Analysis Using Different Techniques

Kirti Singh*, Indu Saini, Neetu Sood

Department of ECE, Dr. B R Ambedkar NIT, Jalandhar, India

*Corresponding author

doi: https://doi.org/10.21467/proceedings.114.15

Abstract

In recent decades, the concept of complex physiological systems has become more and more popular. The evaluation of the biological time series' dynamic complexity is an essential subject with possible applications such as the characterization of physiological states i.e. HRV, BP, and RESP signals and pathological disorders to the measurement of diagnostic parameters. The convergence of several physiological regulation processes is the cause of heterogeneity in cardiovascular time series, that consider many factors and function over several time scales, resulting not only the presence of short-term dynamics but also the coexistence of long-range correlations in various physiological signals. The most popular approach to evaluating the dynamic complexity and irregularity of time series over multiple time scales is entropy based analysis. The most used approach is multiscale entropy (MSE) and refined MSE (RMSE). It is then added to the heart period time series, respiration time series, and blood pressure time series, measured in young subjects and old subjects under resting conditions. This research applies to short-term cardiovascular and cardiorespiratory variability documents that LMSE can better describe physiological processes' behavior causing biological oscillations at various time scales than RMSE.

Keywords: Multiscale Entropy (MSE), Heart Rate Variability (HRV), Blood Pressure (BP), Respiration (RESP), Linear Multiscale Entropy (LMSE), Refined Multiscale Entropy (RMSE).

1 Introduction

All physiological systems has an intrinsic features, which are readily evident in the time period of the variables calculated, depicts dynamical complexity of the system. The physiological systems, including the neurological system, the cardiorespiratory system, and the cardiovascular systems, gives complex signals in the output because of the combined activity of various physiological regulation processes coupled together via functional and structural ways[1]–[4]. Since these numerous and active processes normally operate on different time scales, the interest in statistical methods to evaluate a dynamic oscillation's complexity and irregularity has increased during recent years. Nonlinear analysis approaches and quantifying uncertainty can also be used to recognize the existence of nonlinear HRV underlying dynamics[5]. Previous research suggests that different nonlinearities can exist in various pathophysiological systems, which other nonlinear methods can see of analysis[6]. The research in this context has been discussed in. MSE has been used to determine the complexity of a time series of physiological systems. The time series is observed at the different time scales for which it is served. According to the research, implementation of MSE is very common now a days in several fields of science [7], which made it a dominant method to enumerate the complexity and irregularity of physiological time series [8], [9] and in the analysis of the brain [9], [10] and cardiovascular and cardiorespiratory variability [9], [10] signals. The proposed work aims to test the effect of various estimation methods on the evaluation of nonlinearity and complexity in short-term HRV, BP, and RESP. We compare MSE, RMSE, and LMSE applied to HRV, BP, and RESP time series measured during different physiopathological states (healthy young and aging).

© 2021 Copyright held by the author(s). Published by AIJR Publisher in the "Proceedings of International Conference on Women Researchers in Electronics and Computing" (WREC 2021) April 22–24, 2021. Organized by the Department of Electronics and Communication Engineering, Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, INDIA

Proceedings DOI: 10.21467/proceedings.114; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-947843-8-8

2 Methods

2.1 Multiscale Entropy

According to the study initiated by Costa et al.[11][2], Multiscale entropy is a measure that evaluates the complexity of a process over several time scales. The estimation is based, for one, on the rescaling of the observed process (i.e., on a particular set of time scales) and, by measuring its entropy amount, on determining the changing complexity of the rescaled process.

The multiscale entropy incorporates two procedures:

1. For a time-based series y, multiple time series is constructed by taking an average of data points. These data points must be lying in the non-overlapping windows. The length of window is increasing with the factor τ. So, each element of the considerable time series, $z_k^{(\tau)}$, can be calculated according to the given equation:

$$z_k^{(\tau)} = 1/\tau \sum_{i=(k-1)\tau+1}^{k\tau} y_i \quad (1)$$

Where,

τ = scale factor,

1 ≤ k ≤ N/ τ.

Length of individual series = N/ τ.

If the scale is 1,

considerable time series = original time series.

2. The second method is by calculating Sample Entropy (SampEn)[2], and then it is designed as a function of a given scale factor. Sample Entropy is statistically regular and observes arrangements in a time series and then calculates the degree of regularity and predictableness.

2.2 Refined Multiscale Entropy

Multiscale Entropy has its two drawbacks majorly: the procedure for eliminating the fast temporal scales that tend to introduce spurious oscillations in the rescaled pathophysiological system time series and the fact that the coarse grain threshold parameter is held at an all-time value, which artificially decreases the MSE levels at a growing scale. Valencia et al. [10], implemented new technique named RMSE to overcome the limitations of pre-existing MSE measure. To overcome limitations of MSE, RMSE includes a filtering step to eliminate the occurrence of fast sequential scales from real processes followed by the downsampling process to eliminate redundancy that occurred in the outputs of first step.

The two steps of the process are as follows:

$$y_f(n) = \sum_{i=0}^{q} a(i)y(n-i) - \sum_{k=1}^{r} b(k)\, y_f(n-k), \quad (2)$$

$$y_c(n) = y_f(n\tau), \quad (3)$$

Where

a(i), b(k) = filter coefficients,

q, r = orders.

2.3 Linear Multi-scale Entropy

LMSE is based on the linear autoregressive (AR) model[12]. It assesses the multiscale complexity of linear Gaussian processes. Accordingly, for a process z, the linear autoregressive can be represented as

$$z(n) = \sum_{t=1}^{p} c(t)z(n-t) + d(n), \quad (4)$$

Where

z(n) = order of the process,

Proceedings DOI: 10.21467/proceedings.114
ISBN: 978-81-947843-8-8

Series: AIJR Proceedings
ISSN: 2582-3922

d(n) = an innovation process with the variance σ_e^2,
c(t), (t=1,….,p) = linear regression coefficients [13], which is a function of the lag t,

3 Application to cardiovascular and cardiorespiratory variability series

For demonstrating the implementation of the suggested approach to analyze the cardiovascular and cardiorespiratory variability series. To detect the multiscale complexity of HRV, RESP, and BP, time series were measured using a batch of young and old subjects in a resting state.

3.1 Fantasia Database

Fantasia database is one of the standard databases which the MIT-BIH sets up. The dataset comprises continuous ECG, BP, and RESP of 20 young subjects and 20 old subjects. The age group of young subject is between (21-34 years old) and the age group of elder subject is between (68-85 years old) undergoing 2hrs of the uninterrupted horizontal relaxing position [13]. Each subgroup of the dataset consist of same numbers of women and men. All subjects were instructed to be remained in resting supine position while making them watch the movie named "Fantasia (Disney 1940)" to help wakefulness.

4 Results and discussion

In this study, time domain analysis and frequency domain analysis of electrophysiological signals of standard dataset has been done to extract the features. These features are used in studying the complexity and irregularity of cardio-vascular and cardio-respiratory signals. The tables shown below the different parameters of hrv.

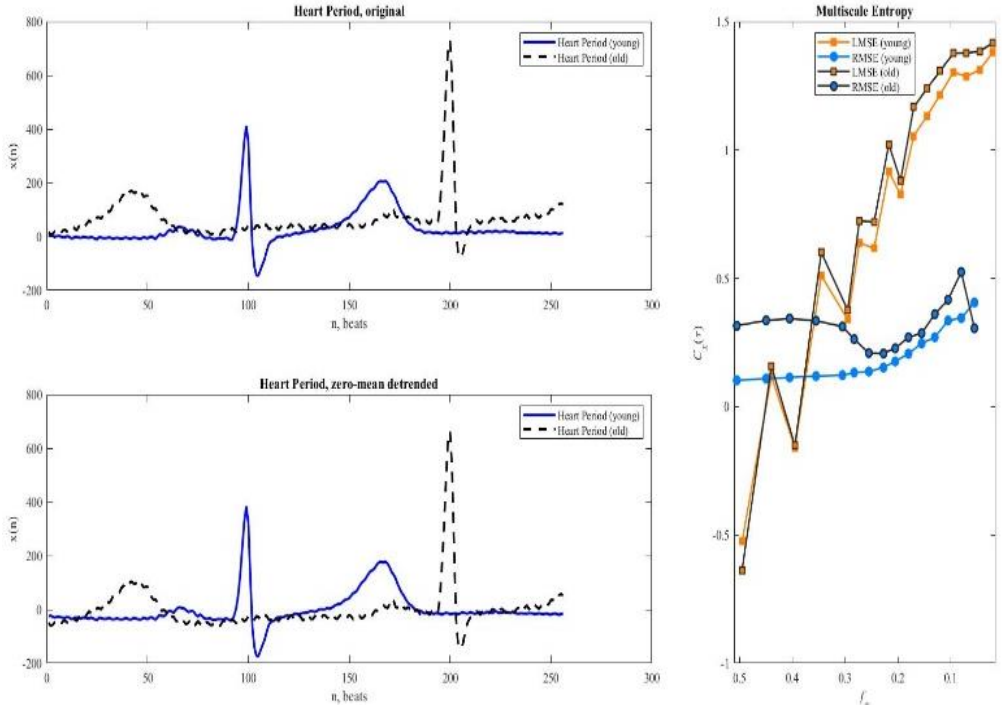

Fig 1. Estimation of MSE for the of heart rate variability time series measurement of young and old age healthy group

This work has explored the various multiscale complexity techniques applied to physiological signals like ECG, BP, and RESP to study their complexity [14], [15]. To examine the efficiency of the mentioned techniques, the techniques have been applied to the young and old healthy subjects of the standard database named "Fantasia Database" and compare LMSE and RMSE on the young and old age group. The multiscale

complexity analysis results of variability in heart rate, respiration, and blood pressure are depicted and represented in fig 1,2 and 3. Fig 1. represents the estimation of multi scale entropy for the time series of HRV. The plot depicts the multiscale entropy estimates ($C_x(\tau_s)$) determined as a function of the cut-off frequency of the LPF in the relaxing supine position for time series of HRV, Respiration, and BPV respectively, to eliminate limitations of multiscale complexity [15][16].

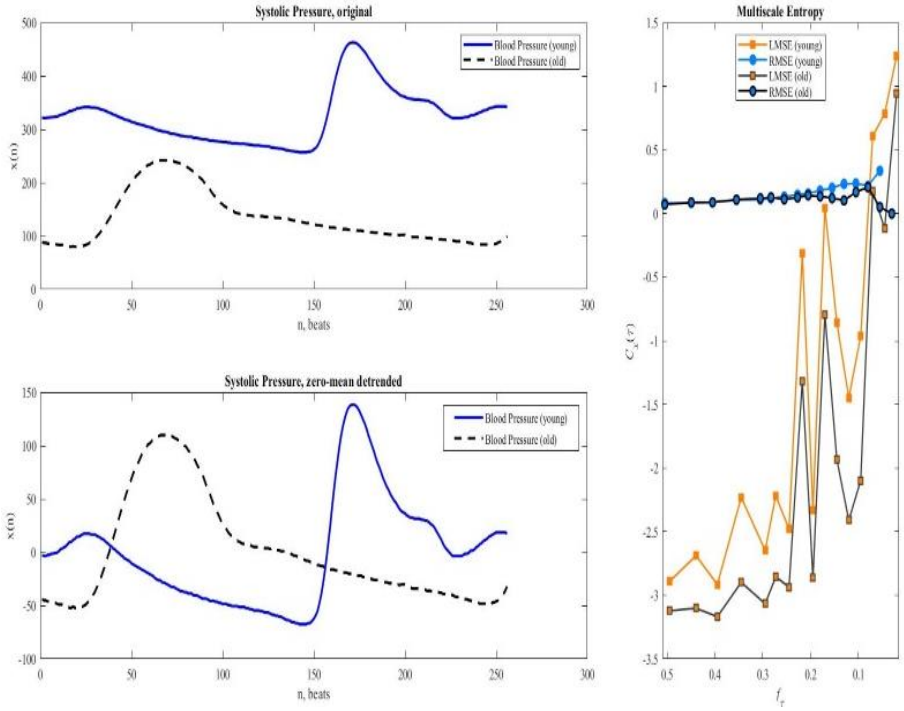

Fig 2. Estimation of MSE for the blood pressure variability time-series measurement of young and old age healthy group

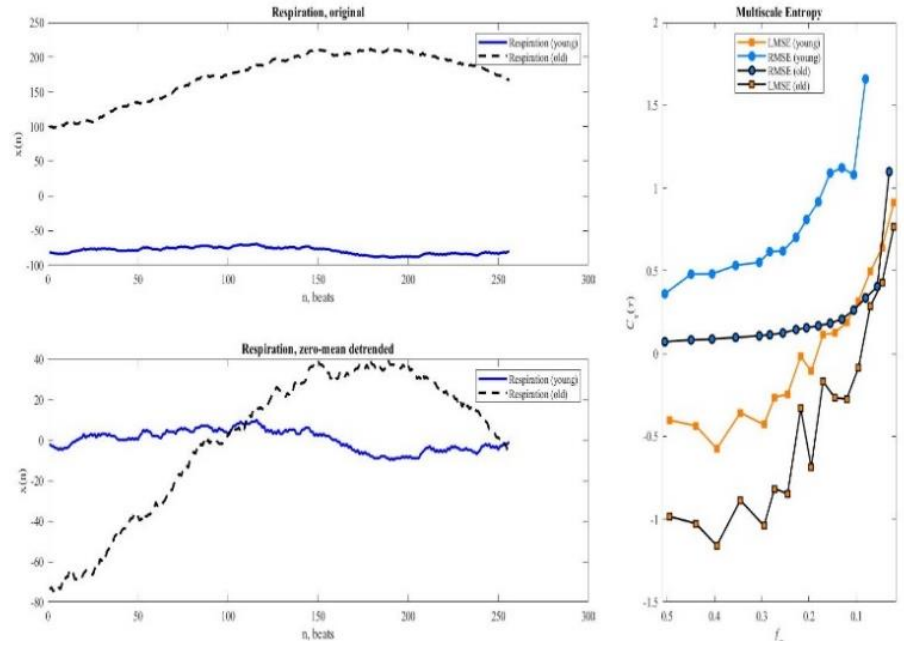

Fig 3. Estimation of MSE for the respiration variability time series measurement of young and old age healthy group

The complexity of HRV in the case of time series of young data is less than that of the old data in both linear multiscale entropy and refined multiscale entropy. The complexity of blood pressure variability and respiratory in case of time series of young data is higher than that of the old data. Some of the parameters of hrv on young and old subjects are represented in the following tables:

Table 1.1: Features extracted using linear analysis on young subjects

	Avg HRV	**Avg HR**	**mean RR**	**mean HRV**
young 1	110.568	9.0433e + 05	110.568	94.3361
young 2	155.2463	6.4511e + 05	155.2463	42.5359
young 3	126.7864	7.6944e + 05	126.7864	148.5908
young 4	162.5637	5.1633e + 05	162.5637	69.8549
young 5	162.4914	5.0201e + 05	162.4914	605.0539
young 6	186.8267	3.6534e + 05	186.8267	60.6535
young 7	130.5377	7.3325e + 05	130.5377	56.3108
young 8	148.8081	6.1106e +05	148.8081	254.948
young 9	165.2909	5.1372e + 05	165.2909	793.3272
young 10	162.5637	5.1633e + 05	162.5637	69.8549

Table 1.2: Features extracted using linear analysis on old subjects

	Avg HRV	**Avg HR**	**mean RR**	**mean HRV**
old 1	131.2581	6.9536e + 05	118.3609	63.6028
old 2	132.0544	7.1058e + 05	132.0544	1100.2506
old 3	130.5699	7.2197e + 05	130.5699	56.7131
old 4	125.4557	7.6128e + 05	125.4557	57.9909
old 5	101.5678	9.9936e + 05	101.5678	1030.7491
old 6	14205480	5.6444e + 05	142.548	45.4732
old 7	134.235	6.4936e + 05	134.235	50.62
old 8	123.2397	7.8178e + 05	123.2397	4.1012
old 9	133.3632	6.9536e + 05	133.3632	83.8666
old 10	101.3874	9.8633e + 05	101.3874	323.5037

5 Conclusion

The study presents the multiscale entropy measure based on the theoretical grounds. It can analytically compute with the help of two methods, i.e., LMSE and RMSE. From the results, it will be observed that the LMSE method is more efficient than MSE and its modification RMSE. It is highly data-efficient in measuring the complexity of the physiological signals such as HRV, RESP, and BP. The above study can be extended in future for the comparison of mentioned techniques with other non-parametric entropy procedures. The future study can help in clarifying the importance of finding non-linearities in the multi-scale time series analysis of physiological systems.

References

[1] W. W. Burggren and M. G. Monticino, "Assessing physiological complexity," *Journal of Experimental Biology*, vol. 208, no. 17. pp. 3221–3232, Sep. 2005, doi: 10.1242/jeb.01762.

[2] A. Bashan, R. P. Bartsch, J. W. Kantelhardt, S. Havlin, and P. C. Ivanov, "Network physiology reveals relations between network topology and physiological function," *Nat. Commun.*, vol. 3, 2012, doi: 10.1038/ncomms1705.

[3] M. A. Cohen and J. A. Taylor, "Short-term cardiovascular oscillations in man: Measuring and modelling the physiologies," *Journal of Physiology*, vol. 542, no. 3. Cambridge University Press, pp. 669–683, Aug. 01, 2002, doi: 10.1113/jphysiol.2002.017483.

[4] A. Porta, M. Di Rienzo, N. Wessel, and J. Kurths, "Addressing the complexity of cardiovascular regulation," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 367, no. 1892. Royal Society, pp. 1215–1218, Apr. 13, 2009, doi: 10.1098/rsta.2008.0292.

[5] R. S. Singh, B. S. Saini, and R. K. Sunkaria, "Times Varying Spectral Coherence Investigation of Cardiovascular Signals Based on Energy Concentration in Healthy Young and Elderly Subjects by the Adaptive Continuous Morlet Wavelet Transform," *Irbm*, vol. 39, no. 1, pp. 54–68, 2018, doi: 10.1016/j.irbm.2017.12.004.

[6] A. Frattola *et al.*, "Time and frequency domain estimates of spontaneous baroreflex sensitivity provide early detection of autonomic dysfunction in diabetes mellitus," *Diabetologia*, vol. 40, no. 12, pp. 1470–1475, 1997, doi: 10.1007/s001250050851.

[7] A. Martins *et al.*, "Multivariate and multiscale complexity of long-range correlated cardiovascular and respiratory variability series," *Entropy*, vol. 22, no. 3, 2020, doi: 10.3390/e22030315.

[8] M. Costa, A. L. Goldberger, and C.-K. Peng, "Multiscale Entropy Analysis of Complex Physiologic Time Series," 2002, doi: 10.1103/PhysRevLett.89.068102.

[9] L. Angelini *et al.*, "Multiscale analysis of short term heart beat interval, arterial blood pressure, and instantaneous lung volume time series," *Artif. Intell. Med.*, vol. 41, no. 3, pp. 237–250, Nov. 2007, doi: 10.1016/j.artmed.2007.07.012.

[10] J. F. Valencia *et al.*, "Refined multiscale entropy: Application to 24-h holter recordings of heart period variability in healthy and aortic stenosis subjects," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 9, pp. 2202–2213, Sep. 2009, doi: 10.1109/TBME.2009.2021986.

[11] A. B. Barrett, L. Barnett, and A. K. Seth, "Multivariate Granger causality and generalized variance," *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.*, vol. 81, no. 4, Apr. 2010, doi: 10.1103/PhysRevE.81.041907.

[12] L. Faes, A. Porta, G. Nollo, and M. Javorka, "Information decomposition in multivariate systems: Definitions, implementation and application to cardiovascular networks," *Entropy*, vol. 19, no. 1, 2017, doi: 10.3390/e19010005.

[13] L. Faes, G. Nollo, and K. H. Chon, "Assessment of granger causality by nonlinear model identification: Application to short-term cardiovascular variability," *Ann. Biomed. Eng.*, vol. 36, no. 3, pp. 381–395, 2008, doi: 10.1007/s10439-008-9441-z.

[14] L. Barnett and A. K. Seth, "Granger causality for state-space models," *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.*, vol. 91, no. 4, Apr. 2015, doi: 10.1103/PhysRevE.91.040101.

[15] W. Xiong, L. Faes, and P. C. Ivanov, "Entropy measures, entropy estimators, and their performance in quantifying complex dynamics: Effects of artifacts, nonstationarity, and long-range correlations," *Phys. Rev. E*, vol. 95, no. 6, Jun. 2017, doi: 10.1103/PhysRevE.95.062114.

[16] L. Faes, A. Porta, M. Javorka, and G. Nollo, "Efficient computation of multiscale entropy over short biomedical time series based on linear state-space models," *Complexity*, vol. 2017, 2017, doi: 10.1155/2017/1768264.