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An Upgraded Entropy and Fractal Investigation of HRV Signal for Identification of Heart Dynamics-A Multiscale Methodology

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Abstract: It's possible that the increased popularity of biomedical engineering is due in part to a number of variables, such as how easy it is to gather the data, how little bandwidth it needs for power-efficient telemetry, and how much interest there is currently in the field. Because of the potential influence that HRV research could have on the health of the autonomic nervous system, both conventional medicine and complementary and alternative medicine have given it a lot of attention (ANS). In order to solve the issue of instability as well as a high level of sensitivity to pre-determined parameters and the duration of the data, a one-of-a-kind multiscale enhanced distribution entropy (ImDistEn) has been developed. In order to offer a more accurate evaluation of the vectors' distribution in phase space, L1-norm distance is employed in conjunction with the ordinal and orientation similarity of embedded vectors. [Case in point:] [Case in point:] [Case in point:] [Cas The proposed ImDistEn parameter has the ability to differentiate between a wide range of synthetic signals, including white Gaussian noise (WGN), chaotic signals (based on both the Logistic map and the two-dimensional Henon map), MIX processes, fractal time series (with varying Hurst exponents), and pink noise at a number of different scales. After being tested on three different HRV datasets, it was discovered that the performance of the algorithm on real-world signals was consistent.

Keywords*: *WGN; ANS; HRV; ImDistEn.

1. Introduction:

Both yoga and meditation have risen to prominence in recent years as people have discovered its beneficial effects on stress levels and mental health. Throughout the past two decades, researchers have investigated HRV signals extensively in an effort to better understand the effects they have on human physiology. In order to better understand ANS activity, the HRV signal may be favoured over other physiological signals because it is simpler to acquire. The significance of ANS in determining the HR supports its use as a marker of ANS. In addition, the acquisition of an HRV signal is significantly simpler and less expensive than the acquisition of other biological signals like an EEG signal or a hormonal analysis based on a blood sample. In 1996, the Task Force on HRV analysis issued recommendations that helped spread the word that analysing HRV signals in the temporal and frequency domains can provide details about the sympathetic nervous system's homeostasis. On the other hand, it is not as simple as it may seem to derive consistent conclusions on the effect of meditation utilising HRV signal. This is due to the fact that meditating may have varied effects on different people, based on factors such as their prior experience with the practise, their level of proficiency, how well they execute, and the differences between their internal and external dynamic interactions When this occurs, it is crucial to separate the artefacts of non-stationary components resulting from external causes from the true changes in the HRV signal. As a non-stationary signal, HRV may benefit more from a segment-by-segment analysis. Changes in breathing rate, posture, and mental state are the three primary contributors to the shift in RR interval variability that occurs during the practise of meditation and yoga.

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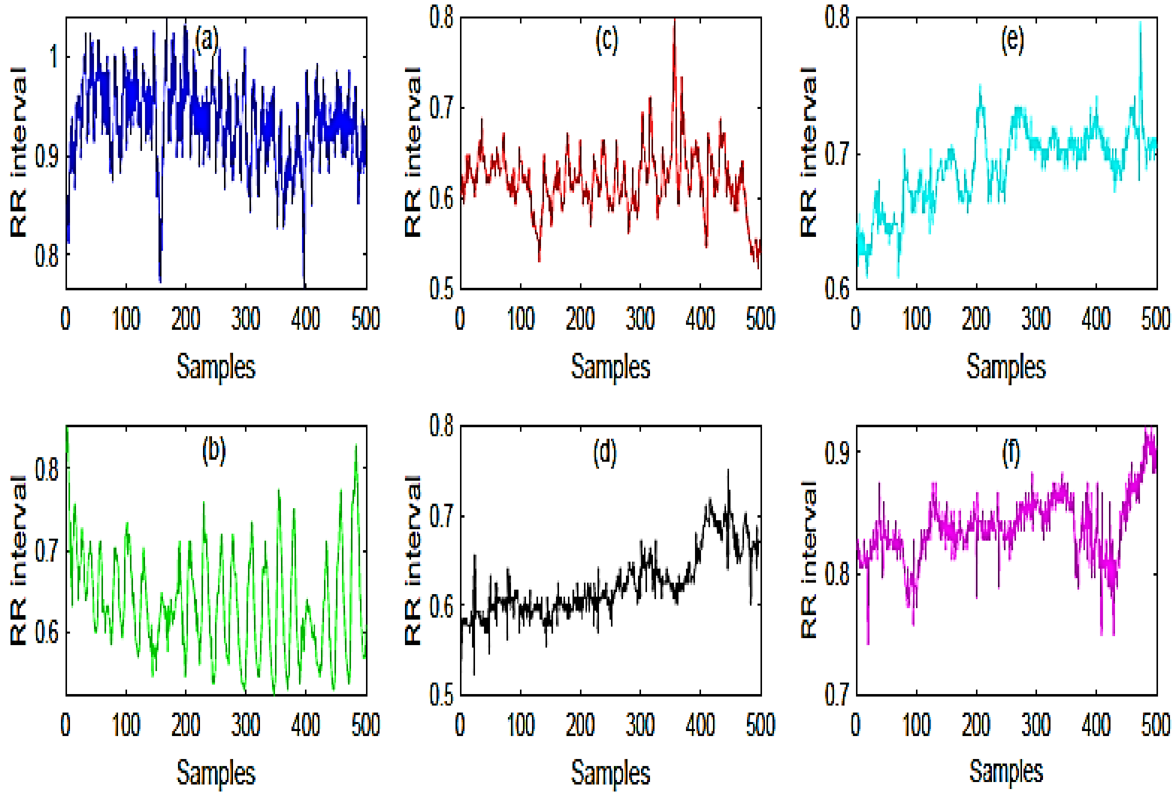

Fig I: Representative HRV signals of (a) meditator before meditation, (b) meditator during meditation, (c) normal subject, (d) high-risk hypertensive patient, (e) CHF persistent, and (f) persistent having paroxysmal atrial fibrillation.

There are various kinds of HRV indicators because linear time domain analysis measures RR interval variability from various angles. These indices are often calculated with normal (no ectopic) beats as the basis. An ectopic beat is replaced with a normal beat using a pre-processing technique so that the data has normal to normal (NN) intervals. Several time-domain indices and parameters are derived from these NN intervals using statistical and geometrical techniques. In order to analyse HRV, geometrical approaches use patterns of geometry in conjunction with the parameters derived from the probability distribution of NN intervals. They use the probability distribution to determine values such as the bin width that corresponds to the frequency of observation indicated, various geometrical parameters based on the approximation of the shape of the distributions, etc.

Conventional spectrum analysis methods, however, have the significant drawback of assuming that the signal being analysed is steady. Yet, in practise, HRV, like most biological signals, is non-stationary, meaning that its behaviour varies slightly from segment to segment. More insight can be gained from the analysis of a non-stationary signal, such as HRV, by employing a time-frequency representation-based approach. Possibly as a result, current efforts on spectral analysis of HRV have relied heavily on tools like the wavelet transform (WT), empirical mode decomposition (EMD), and variational mode decomposition (VMD). When discussing WTs, the continuous wavelet transform (CWT) and discrete wavelet transform (DWT) are two of the most common methods. Because it only uses the approximate coefficients of a decomposed signal and ignores the detail coefficients, CWT provides arbitrarily high frequency resolution, while DWT provides excellent computational efficiency with restricted frequency resolution. Most signals can be effectively analysed with DWT as long as the depth of decomposition is set to the level you need. However, DWT can lead to mixing of high frequency and low frequency components of HRV spectra under the same DWT coefficient, which is problematic for analysing HRV signals. WPT's great frequency resolution may make it particularly useful for evaluating low frequency signals like HRV. While WTs necessitate that you pick an appropriate analysis function, EMD, VMD, and the empirical wavelet transform (EWT) are all based on adaptive decomposition techniques that eliminate this step. While these techniques have seen significant use, they still have limitations when it comes to isolating small differences in frequency.

In this research, we will offer robust HRV markers to capture the nonlinear dynamics of HRV signal and the assessments of its dynamical complexity. With the goal of enabling strong differentiation between signals of various natures and degrees of complexity, a new entropy parameter, improved multiscale distribution entropy (ImDistEn), is presented. The proposed entropy marker's secondary goals are to decrease its susceptibility to fixed parameters and increase its stability over short data lengths. In order to do this, we extract the embedded vectors (in phase space representation) from the time series and analyse their properties. A novel distance metric is constructed using the l1-norm plus angular and ordinal information. The probability distribution of this metric is evaluated. Three real-world signals are used to examine the effectiveness of the ImDistEn parameter using a t-test with a significance level of 0.01. To better examine the multifractal nature of HRV signals with shorter data sets, a novel multifractal analytic method is also proposed.

What follows is the outline for the rest of the chapter. The related work is briefly described in Part 2, and the methodology and theoretical foundations of the methods used are described in Section 3. The simulation results and analyses are presented in Section 4. For the chapter's final section, "Key Findings," we summarise the most important results.

2. Existing Work Done:

Using multiscale entropy (MSE) analysis, we may ascertain whether or not supplementary information is distributed across multiple temporal scales in the signal, or whether it is localised to a single scale. However, there are a few problems with entropy-based evaluation and differentiation of signals; these include instability, sensitivity to short data length, noise, and tuning parameters. Two widely used indices, approximate entropy (ApEn) and sample entropy, were used to evaluate the dynamical complexity of the HRV signal (SampEn). In phase space, they measure the complexity of a signal by the distance between its embedding vectors at each unit-size step. Despite their widespread application in HRV-based disease detections, they suffer from the drawback of producing unpredictable outcomes for short time series data. About the threshold distance r, which is highly sensitive to a chosen parameter, is also important. Permutation entropy (PEn), calculated from ordinal rankings, is more reliable in this setting.

Nevertheless, it cannot analyse time series with a string of consecutively equal values, nor can it determine the direction in which changes in amplitude actually take place. The increment entropy, the refined composite PEn (RCMPE), and the weighted PEn are also offered as enhancements. Symbolic entropy (SymDynEn), base-scale entropy (BsymEn), dispersion entropy (DispEn), and slope entropy (SlopEn) are all examples of entropy measures that use a signal's symbolic representation. Distribution entropy (DistEn) is a new entropy proposed by the authors to address the sensitivity problem with ApEn and SampEn. Its multiscale variant (MDistEn) is proposed by Lee and Choi [33]. In contrast to ApEn and SampEn, which only take into account distances that are less than some threshold r, the DistEn algorithm makes use of the PDF of vector distances. DistEn, however, ignores angular and ordinal data. Hence, while it can provide a reliable estimate of the complexity of many signals, it is unable to differentiate chaotic, white Gaussian noise (WGN), and MIX (combination of periodic and random) processes at numerous scales. With these problems plaguing current entropy markers, it is crucial to develop an entropy marker that can reliably reveal the full complexity of HRV signals and time series, even when dealing with limited amounts of data. Fractal and multifractal behaviour in HRV signals, and how they change in response to pathological states of the heart, is another interesting feature of HRV signals. Fractal or self-similarity activity is observed in a wide variety of natural objects and signals, including mountains, leaves, DNA sequences, network traffic time series, etc. Since the HRV signal is the scatter plot of RR interval variability against the time of occurrences of RR intervals, we can more accurately refer to it as a self-affine fractal. Fractal characteristics of the HRV signal vary from one segment to the next because of its non-stationary nature. Hence, the fractal nature of an HRV signal cannot be completely described by a global scaling exponent for all the segments. In this case, a multifractal analysis of the HRV signal is required. Due to the presence of varied trends, which need to be detrended before analysis, DFA-based approaches detect more significance for HRV signals. Linear, quadratic, or higher order regression methods are commonly used to detrend HRV signals, while EMD-based, wavelet-based, or smoothness priors-based methods are typically employed to detrend other biological signals. Across a range of window sizes, linear regression methods appear to struggle to adequately capture the trend. The computational complexity grows proportionally with the order of the regression. However, the maximum and minimum envelopes of the HRV signals are often captured by wavelet or EMD-based algorithms. Finding the right detrending method for HRV signals is a crucial challenge under these conditions. In addition, the data lengths of HRV signals can range from a few minutes to a few hours, whereas the minimal data length for multifractal analysis in practise is often around 8000 samples. We suggest a straightforward method for detrending that makes use of a low-pass filter and, unlike previous methods, use a window that overlaps with the data rather than a series of non-overlapping windows, therefore resolving these two major concerns.

3. The Proposed Algorithm:

Across a range of window sizes, linear regression methods appear to struggle to accurately capture the trend. Computational complexity grows as the order of regression rises. However, the maximum and minimum envelopes of the HRV signals are often captured by wavelet or EMD-based algorithms. Finding the appropriate detrending method for HRV signals is thus a significant problem under such conditions. The data lengths of HRV signals can range from a few minutes to many hours, whereas the minimum data length for multifractal analysis in use is typically 8000 samples. To address these two major challenges, we present a low-pass filter-based overlapping window detrending method, which is both straightforward and effective.

In light of the foregoing, we first describe the proposed multiscale entropy analysis method, and then the multifractal analysis method, both of which are applied to HRV data. We begin with a quick introduction to data pre-processing, followed by a presentation of pertinent existing techniques and, finally, the proposed methods. The l1-norm, angular (orientation-based), and Spearman (ordinality-based) distance information for embedded vectors in the phase space domain are utilised in the suggested entropy measure, entitled improved distribution entropy (ImDistEn). This proposed entropy is developed to extract comprehensive details of the test signals under examination by linearly combining the vector distances to get a weighted average distance. By processing normalised first-order difference (FOD) time series, ImDistEn may provide an objective estimation of the complexity of signals in a wide variety of domains and at varying amplitudes.

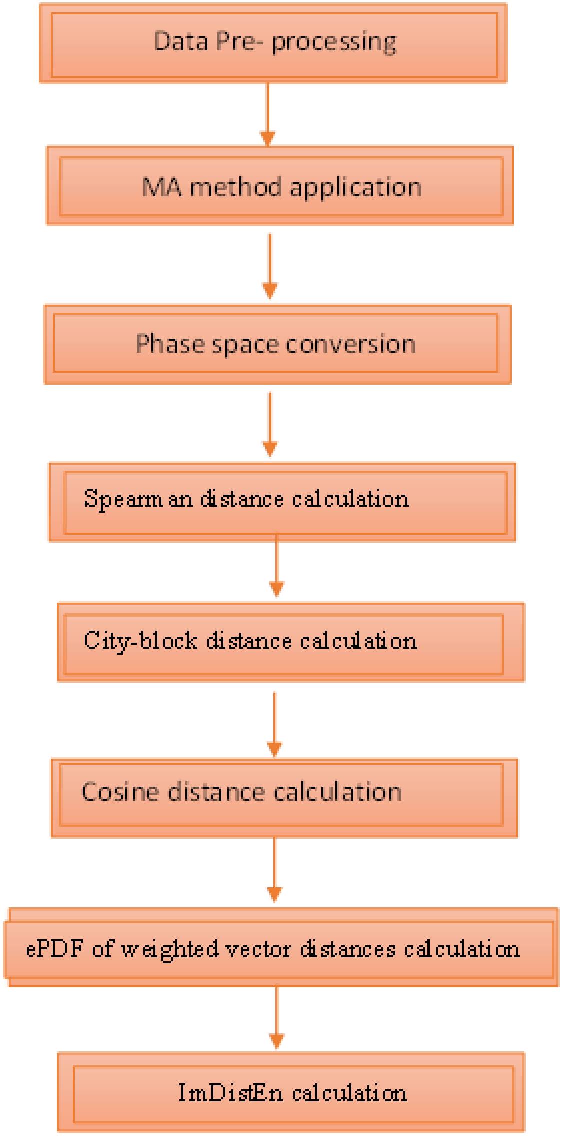

Fig II: The Proposed Block Diagram.

Then, the suggested ImDistEn is formulated using the FOD series by performing the following steps:

Step 1: It is about multiscale analysis, a moving average (MA) technique is used to partition a series of normalised FOD (nFOD) values. When a time series is normalised, the data points are transformed into uniform intervals of similar amplitude.

Step 2: A time series must be transformed into the phase space form in order to capture the correlation behaviour between the samples and to also study their temporal structure.

Step 3: The Spearman distance is calculated to investigate the ordinal patterns of the vectors; this distance is the measure of the similarity between two vectors in terms of their ordinal positions.

Step 4: we may use the city-block (CB) (or l1-norm) distance to determine how far apart vectors of time delays are in all embedding dimensions.

Step 5: The cosine of the angle between two embedded vectors provides the distance metric.

Step 6: The ePDF of weighted vector distances can be calculated by using the upper/lower triangular members of the Da(i, j) matrix.

$$D_a(i,j) = \frac{w_1 D_S(i,j) + w_2 D_b(i,j) + w_1 D_c(i,j)}{w_1 + w_2 + w_3} \quad (1)$$

Where,

$D_s(i,j)$: Spearman distance

$D_b(i,j)$: City-block distance

$D_c(i,j)$: Cosine distance

w_1, w_2, w_3= Weight Vectors

$$ImDistEn = -\sum_{i=1}^{M} P \log P \quad (2)$$

Due to its non-stationary nature, HRV signals necessitate detrending in order to remove the noise introduced by the underlying dynamics during analysis. An LPF, or low pass filter, is a tried and true method of filtering out information that occurs at frequencies over a specified threshold. HRV signals have a known frequency range, hence low-order low-pass filters (LPFs) work well for this purpose.

4. Result and Discussion:

The effectiveness of the suggested ImDistEn is measured using a variety of synthetic time series data that follows industry standards. We have created 50 realisations of each synthetic signal with data lengths (N) ranging from 50 to 1500 in order to study the sensitivity of the proposed ImDistEn to signal length.

Table I: Normalized entropy measures Comparison.

Data Length	Chaotic (Entropy)			WGN (Entropy)		
	RCMDE	**MDistEn**	**ImDistEn**	**RCMDE**	**MDistEn**	**ImDistEn**
100	0.51	0.91	0.93	0.76	0.87	0.93
200	0.53	0.93	0.95	0.86	0.89	0.94
300	0.52	0.95	0.95	0.96	0.88	0.95
500	0.54	0.94	0.96	0.98	0.87	0.94
700	0.56	0.95	0.95	0.97	0.85	0.95
1000	0.55	0.95	0.96	0.98	0.84	0.96

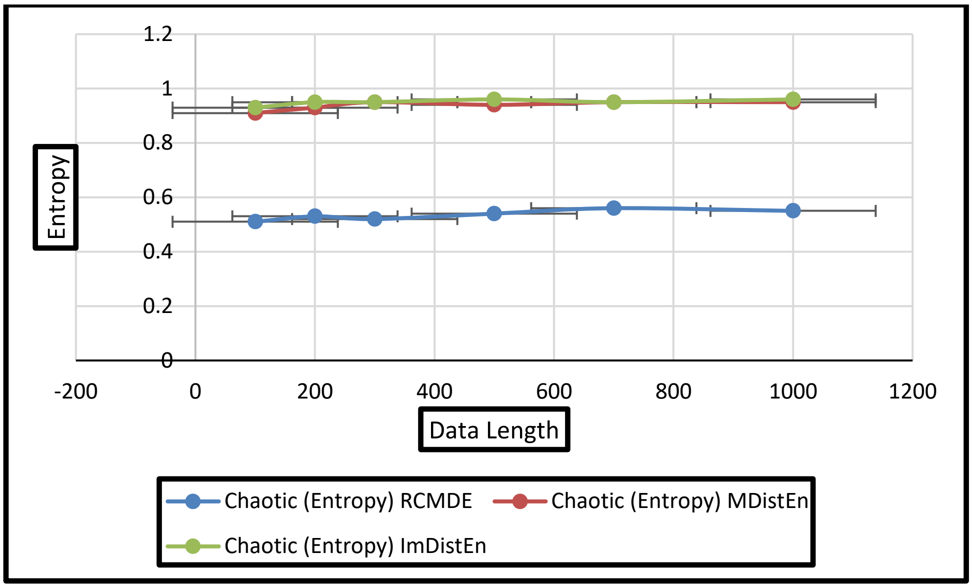

Fig II: Normalized entropy measures for logistic-map based chaotic.

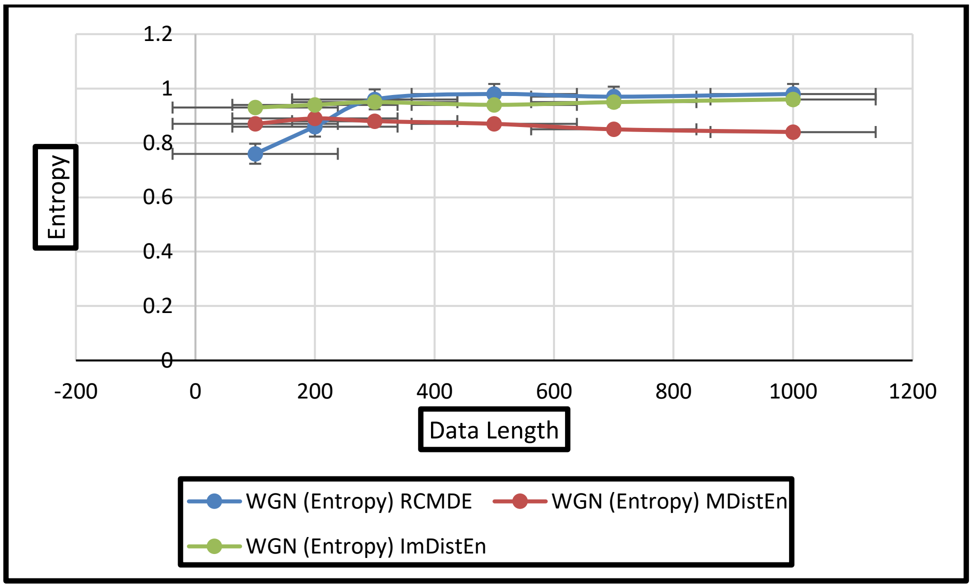

Fig III: Normalized entropy measures for WGN.

In Figure II and Figure III, we have a visual representation of the entropy's relationship to the data's length. It demonstrates that very short data lengths yielding very small standard deviations have a negligible impact on ImDistEn, MDistEn, and RCMPE. Yet, for all three types of signals, RCMDE-based metrics show a decrease in fluctuations after N >= 700. Consequently, we have set N = 500 to assess their capacity to differentiate between signals of varying complexity and origin.

Nonetheless, the suggested ImDistEn measure has performed better than the state-of-the-art methods on all three datasets. In Table II, we can see that the computation time for ImDistEn is significantly higher than that of the other methods.

Table II: Computation time of entropy measures for scale=20 and *m*=3.

Entropy	Computation time (sec) for different data length			
	100	200	500	1000
MDistEn	0.12	0.17	0.28	0.67
ImDistEn	0.28	0.36	0.65	1.19
RCMDE	0.28	0.35	0.44	0.65

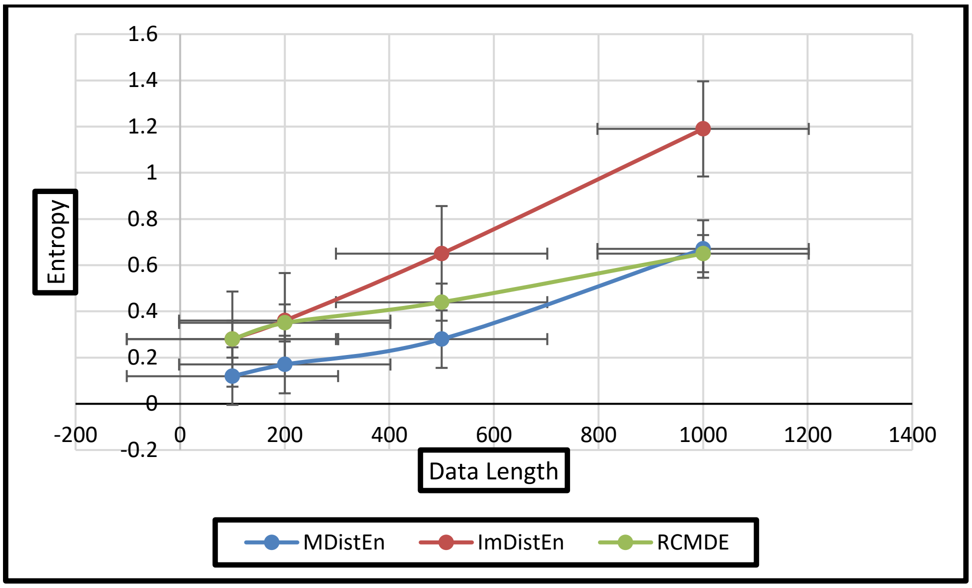

Fig IV: Computation time of entropy measures Comparison.

In this paper, we introduce a brand new complexity descriptor called ImDistEn with the intention of giving a valid categorization between signals of varied degrees of complexity. For the purpose of illuminating the intrinsic motion of a signal, the proposed marker makes use of the angular, ordinality, and l1-norm distance information contained within the signal's embedded vectors. It has solved the issue of MDistEn by illuminating the distinctions between WGN, 1/f noise, and chaotic signals at a variety of length scales, which was the difficulty that MDistEn was trying to tackle. It is also able to accurately differentiate between the study group and the control group when it is applied to datasets derived from the actual world.

We have performed statistical significance tests on the characteristics recovered from the multifractal analyses; the paired t-test for the MEDITATION dataset and the independent t-test for the PAF datasets, respectively. Based on the results of Table III, it appears that the MFDFA method has been successful in distinguishing between the meditative and pre-meditative states when the Ws and value is less than 5, but that it has been less successful in distinguishing between the PAF and CHF data and the healthy data in other respects.

Table III: Variation of scaling exponents with respect to *q* for meditative and pre-meditative HRVs using MFDFA and proposed method.

S. No.	Q Value	MFDFA method		Proposed method	
		Pre-Meditation	Meditation	Pre-Meditation	Meditation
1	-5	1.81	2.0	1.11	1.62
2	-3	1.79	1.98	1.15	1.61
3	-1	1.76	1.96	1.21	1.51
4	0	1.78	1.82	1.10	1.45
5	1	1.77	1.75	0.98	1.20
6	3	1.75	1.71	0.97	1.12
7	5	1.74	1.65	0.96	0.95

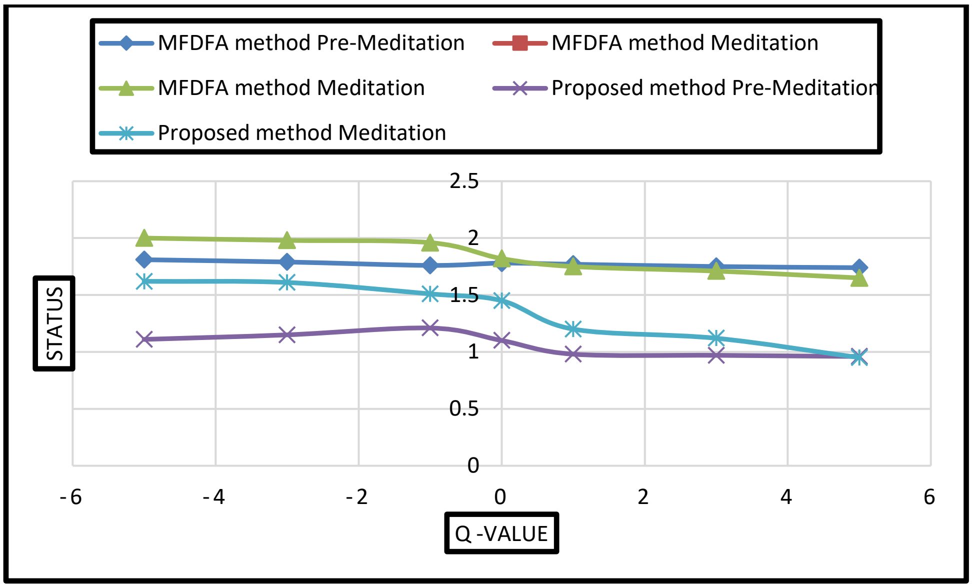

Fig V: Variation of scaling exponents with respect to *q* for meditative and pre-meditative HRVs using MFDFA and proposed method.

5. Conclusion:

The complexity of the HRV signal's dynamics can shed light on heart physiology in novel ways. The dynamical complexity of the HRV signal has been quantified using the idea of mono/multiscale entropy. Analysis of the signal using multiscale entropy (MSE) can reveal whether or not extra information is distributed across multiple time scales. However, there are certain problems, including instability in entropy-based evaluation/distinction of signals and susceptibility to short data length, noise, and tuning parameters. With the goal of providing reliable classification between signals of varying complexity, we present a new complexity descriptor (ImDistEn) in this study. The suggested marker makes use of a signal's embedded vectors' angular, ordinality, and l1-norm distance information to reveal the signal's intrinsic motion. It has solved the problem of MDistEn by elucidating the differences between WGN, 1/f noise, and chaotic signals at various length scales. When applied to real-world datasets, it is also able to accurately distinguish between the study and control groups. Also, we provide a multifractal analytic technique that yields consistent outcomes with significantly less data (data length 1000 data points). We put the suggested multifractal approach through its paces with both synthetic and real-world HRV data. Statistical significance tests and experimental results show that it can discriminate between normal and abnormal heart states by characterising various fractal data.

Conflict of Interests:

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

Ethical approval:

This article does not contain any studies with human participants or animals performed by any of the authors.

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