



Comparative Analysis of Rescaled Range Results of Normal and Abnormal Heart Sound Recordings

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Authors' contributions

This work was carried out in collaboration between both authors. Author LI designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author TAOS managed the analyses of the study. Both authors read and approved the final manuscript.

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ABSTRACT

Heart acoustics can be used as an early diagnostic tool, to quickly and accurately identify medical patients who may be at risk of unfavourable cardiovascular outcomes. However, at present, there remains no universally accepted standard or technique for detecting abnormalities using Phonocardiograms. To address this, a large database containing normal and abnormal heart sound recordings of patients were studied with the rescaled range technique and the Hurst exponent, a measure of persistence for non-linear dynamic data. Using the Hurst exponent (H) as a benchmark, we compared the values of the Hurst exponent for normal heart sound recordings with that of the abnormal heart sound recordings. For this study, the recording length was limited to the first 10 seconds for all 578 distinct recordings, which were selected randomly from the database. Furthermore, two Hurst exponent values were obtained for each recording, by subjecting them to time intervals of 1 and 2 milliseconds respectively. The results from this study show that heart sound recordings are persistent ($H > 0.5$) for normal and abnormal heart sound recordings, with the normal recordings being slightly more persistent.

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ABBREVIATIONS

R : Widest Spread (maximum value - minimum value);
S : Standard deviation;
T : Study data length (Minimum allowed in the study was 2);
H : Hurst Exponent;
K : Constant of Proportionality;
s : Seconds;
ms : Milliseconds;
PCG : Phonocardiogram;
ECG : Electrocardiogram;
CVD : Cardiovascular Disease;
MRI : Magnetic Resonance Imaging;

1. INTRODUCTION

According to the World Health Organization's 2015 report, nearly 17.5 million people died from different types of cardiovascular diseases (CVD) in the year 2012, which represents 31% of global deaths [1]. While Electrocardiograms, Computed Tomography scans and MRIs exist for the detection of CVDs, these methods are expensive in Low to Middle-Income countries (LMICs) and also require a trained hand. On the other hand, methods for automatic stratification of heart sound recordings often suffered from a lack of robustness because of the limited database available.

The 2016 PhysioNet Computing in Cardiology (CinC) Challenge addressed this issue by providing the largest dataset to date of heart sound recordings along with a common platform for the evaluation of algorithms. The data was drawn from multiple research groups across the world, recorded in various clinical and non-clinical environments [2]. Although various kinds of heart pathology exist, the challenge classifies all recordings as “normal” and “abnormal”.

Majority of the research groups that participated in the 2016 Physionet CinC Challenge attempted to classify recordings either by segmentation, feature extraction or a combination of both. Ortiz et al. [3], for example, classified Phonocardiogram (PCG) recordings by first segmenting and extracting features before using a supervised learning method. Tang et al. [4], use 324 features extracted from multi-domains of each recording to train a backpropagation neural

network for the prediction and obtain an overall score of 83.6% on the Physionet CinC performance scale. Tschannen et al. [5], developed a model that relies on a robust feature representation - generated by the wavelet-based deep convolutional neural network - of each cardiac cycle in the test recording, and support vector machine classification.

With this in mind, this paper aims to study short unsegmented PCG recordings using the rescale range technique and the Hurst exponent index to measure the degree of persistence of both classes of recordings and establish a relationship between Hurst exponent values for normal and abnormal heart sound recordings. For a more comprehensive review of prior work on heart sound classification, refer to Liu et al. [6].

2. METHODOLOGY

Three assumptions were made before implementing the rescaled range and Hurst exponent algorithm. The first is that a valid conclusion can be made about the nature of a heart recording in 10 seconds. This was done to have a uniform recording length that is consistent with all recordings studied. Based on previous literature Nilanon et al. [7], medical practitioners concur with this assumption. Another assumption is that the behaviour of a particular recording would remain the same for a small change in the time interval. The final assumption is that heart sound recordings can be accurately studied without segmentation.

We begin this section by describing the data used in this study, then the methods used for processing the data and the final algorithm adopted.

2.1 The Dataset

Six datasets consisting of a total of 3,126 Phonocardiograms were provided for study in the Physionet 2016 CinC databanks [8]. All recordings contain a single lead, which was acquired from one of nine locations on the body. Upon review of the distribution of normal vs. abnormal records in the various databases, we created a balanced dataset consisting of an equal number of abnormal recordings as shown in Table 1.

2.2 Data Cleaning

"Noise" which is present in some of the recordings provided reduces the accuracy of the analysis used in this study and some cases prevents the execution of the rescaled range technique. As a result of this, a method of detecting and eliminating noisy signals was developed. This process is illustrated by the flowchart in the Appendix-I.

2.3 The Rescale Range Analysis

For the rescale range the method used is such that Hurst exponent is computed for each recording studied. The rescaled range depends on the lengths of time (range) to be analysed. A recording length of 10 seconds corresponds to a data length of 20,002. To obtain a well-structured range, the logarithm of the size of the entire data series for each recording was divided by the logarithm of two, which yields 14.29. This value was then rounded down to its nearest whole number, after which the new data length became two raised to the power of the rounded down number. This gives a new data length 16,384, which is a multiple of 2 and allows for easy and consistent division of ranges. Given the new data length of 16,384, we divided into non-overlapping ranges of $16,384/v$. With v being a multiple of 2, such that the size of each range is also an integer and 2. This yields a total of 13 distinct ranges.

The mean for each range is calculated. A series of deviations for each range was created afterwards, followed by computation of the running total of deviations from the mean.

From these values obtained, the minimum and maximum deviations, as well as the variance and standard deviation were calculated.

The rescaled range is obtained by dividing the widest spread (maximum-minimum deviations) by the Standard deviation. Since there are thirteen ranges per recording, the average rescaled range value was then computed.

2.4 The Hurst Exponent

The rescale range analysis is based on the proportional relationship between the ratio of widest spread (R) and standard deviation (S) to a power of the data length (T). As established in the literature Scheinerman, [9], the model could be represented as;

$$\frac{R}{S} \propto T^H \quad (1)$$

Equation (1) can then be expressed as:

$$\frac{R}{S} = KT^H \quad (2)$$

Where K = constant of proportionality

Taking the logarithm of both sides of the equation we obtain:

$$\text{Log} \frac{R}{S} = \text{Log} (K) + H \text{Log} (T) \quad (3)$$

From equation (3), we see that the behaviour of the graph is a straight line on a log-log graph with a slope of the line being H. The interpretation of the Hurst exponent is as follows:

- $H = 0.5$; is the Hurst exponent value for an uncorrelated time series data or a random walk.
- $H > 0.5$; is the Hurst exponent value for a positively correlated time series (persistence).
- $H < 0.5$; is the Hurst exponent value for a negatively correlated time series (anti-persistence).

Table 1. The distribution of normal and abnormal recordings studied

| Database name | Raw recordings | | | Recordings after balanced | | |
|---------------|----------------|------------|-------------|---------------------------|------------|------------|
| | Abnormal | Normal | Total | Abnormal | Normal | Total |
| Training - a | 292 | 117 | 409 | 117 | 117 | 234 |
| Training - b | 104 | 386 | 490 | 104 | 104 | 208 |
| Training - c | 24 | 7 | 31 | 7 | 7 | 14 |
| Training - d | 28 | 27 | 55 | 27 | 27 | 54 |
| Training - f | 34 | 80 | 114 | 34 | 34 | 68 |
| Total | 482 | 617 | 1099 | 289 | 289 | 578 |

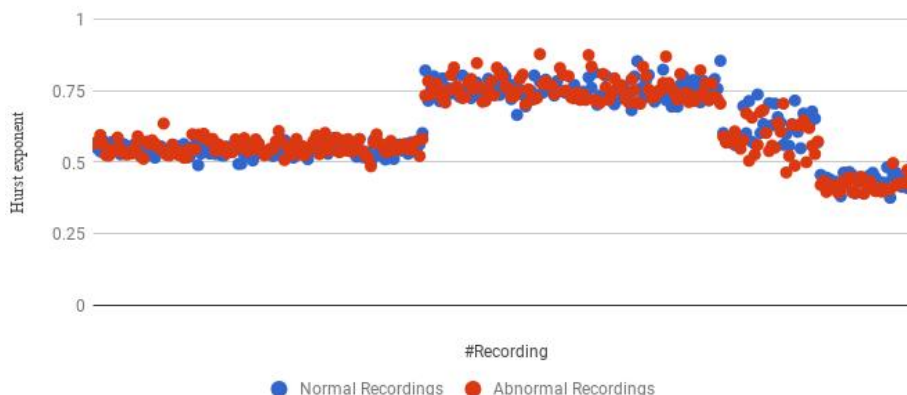


Fig. 1. Distribution of Hurst exponent values for all normal and abnormal recordings for a recording length of 1 millisecond

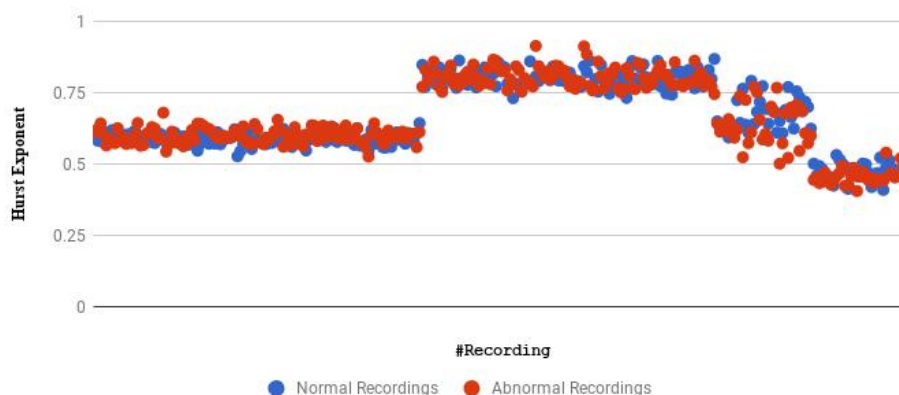


Fig. 2. Distribution of Hurst exponent values for all normal and abnormal recordings for a recording length of 2 milliseconds

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3. RESULTS AND DISCUSSION

3.1 Summary Statistics for Hurst Exponent Values

The analysis from this study are presented in the two tables and four graphs shown below; Table 2 shows the average Hurst exponent values and standard deviation for all recordings for a time intervals of 0.001 seconds and 0.002 seconds, grouped by their respective datasets. The summary of the Hurst exponents obtained for all datasets studied is presented in Table 3.

Table 2. Summary statistics of the Hurst exponents obtained for each dataset studied

| Dataset | Status | Interval (s) | Mean | Mean standard deviation | Minimum | Maximum |
|---------|----------|--------------|-----------|-------------------------|-----------|-----------|
| A | Normal | 0.001 | 0.5435341 | 0.0200409 | 0.4902237 | 0.6021861 |
| | | 0.002 | 0.5898815 | 0.0202051 | 0.5273449 | 0.6434493 |
| | Abnormal | 0.001 | 0.5546495 | 0.0250795 | 0.4862667 | 0.6357163 |
| | | 0.002 | 0.5988496 | 0.0258019 | 0.5264373 | 0.6800612 |
| B | Normal | 0.001 | 0.7554436 | 0.0354021 | 0.6656734 | 0.8546324 |
| | | 0.002 | 0.8030550 | 0.0309028 | 0.7308952 | 0.8683815 |
| | Abnormal | 0.001 | 0.7578076 | 0.0408011 | 0.7028652 | 0.8780071 |
| | | 0.002 | 0.8048827 | 0.0344775 | 0.7455658 | 0.9139944 |
| C | Normal | 0.001 | 0.5757435 | 0.0129669 | 0.5608217 | 0.6024532 |
| | | 0.002 | 0.6219334 | 0.0181013 | 0.5931724 | 0.6497963 |
| | Abnormal | 0.001 | 0.5779774 | 0.0188908 | 0.5477701 | 0.6082068 |
| | | 0.002 | 0.6260759 | 0.0212937 | 0.5925393 | 0.6575915 |
| D | Normal | 0.001 | 0.6352391 | 0.0544967 | 0.5492190 | 0.7369196 |
| | | 0.002 | 0.6864629 | 0.0546633 | 0.6083974 | 0.7917598 |
| | Abnormal | 0.001 | 0.5870008 | 0.0656160 | 0.4647437 | 0.7050888 |
| | | 0.002 | 0.6395723 | 0.0788215 | 0.5013559 | 0.7707597 |
| F | Normal | 0.001 | 0.4367924 | 0.0244375 | 0.3763507 | 0.4830439 |
| | | 0.002 | 0.4745683 | 0.0301264 | 0.4096966 | 0.5318554 |
| | Abnormal | 0.001 | 0.4217356 | 0.0234935 | 0.3904916 | 0.4974239 |
| | | 0.002 | 0.4564095 | 0.0268720 | 0.4056939 | 0.5401025 |

Table 3. The average Hurst exponent values for all normal and abnormal heart sound recordings for time intervals of 0.001 seconds and 0.002 seconds

| Status | Time Interval = 0.001 seconds | | Time Interval = 0.002 seconds | |
|--------------------------|-------------------------------|--------------------|-------------------------------|--------------------|
| | Mean | Standard Deviation | Mean | Standard Deviation |
| Abnormal heart recording | 0.61570881 | 0.12111164 | 0.66069933 | 0.12411861 |
| Normal heart recording | 0.61658211 | 0.11819548 | 0.66282773 | 0.12010887 |

It is observed from Table 3 that the Hurst exponents for both normal and abnormal recordings (0.001 seconds) are both greater than 0.5, that is, $H > 0.5$, with the values ranging from 0.61570881 (Abnormal heart recording) to 0.61658211 (Normal Heart recording). This implies that both the normal and the abnormal heart recordings on average exhibit persistence. In more detail, the implication of these values for their Hurst exponents is that, a high signal measured by the digital Phonocardiogram is likely to be followed by another high signal in the short period, and that this property, by inference is common to both the abnormal and normal heart recordings.

Similarly, from Table 3; it is observed that the Hurst exponents for both normal and abnormal recordings (0.002 seconds) are both greater than 0.5, that is, $H > 0.5$, with the values ranging from 0.66069933 (Abnormal heart recordings) to

0.6628773 (Normal Heart recordings). This implies that both the normal and the abnormal heart recordings also exhibit persistence for a time interval of 0.002 seconds.

From Table 3, the following can be inferred:

1. The average Hurst exponent values for an abnormal heart recording measured with an interval of 0.001 seconds (standard) can be written as 0.61570881 (+ or - 0.12111164).
2. The average Hurst exponent values for a normal heart recording measured with an interval of 0.001 seconds (standard) can be written as 0.61658211 (+ or - 0.11819548).
3. The average Hurst exponent values for an abnormal heart recording measured with an interval of 0.002 seconds can be written as 0.66069933 (+ or - 0.12411861).

4. The average Hurst exponent values for an abnormal heart recording measured with an interval of 0.002 seconds can be written as 0.66282773 (+ or - 0.12010887).

The percentage of persistent correlation for the normal and abnormal recordings is expressed below:

1. Percentage persistent correlation for an abnormal heart recording measured with a time interval of 0.001 seconds: $(0.61570881 - 0.5) / 0.5 = 0.23141762$ (23.14%).
2. Percentage persistent correlation for a normal heart recording measured with a time interval of 0.001 seconds: $(0.61658211 - 0.5) / 0.5 = 0.23316422$ (23.32%).
3. Percentage persistent correlation for an Abnormal heart recording measured with a time interval of 0.002 seconds: $(0.66069933-0.5)/ 0.5 = 0.32139866$ (32.14%).
4. Percentage persistent correlation for a normal heart recording measured with a time interval of 0.002 seconds: $(0.66282773-0.5)/ 0.5 = 0.32565546$ (32.57%).

4. CONCLUSION

In this work, normal and abnormal heart sound recordings have been studied comparatively using a robust non-linear technique. Normal and Abnormal heart sound recordings are persistent in the time intervals studied, which implies that forecasting is possible for both classes of heart recordings. Concerning their index of dependence, we conclude that both classes of recordings behave in a quasi-similar fashion.

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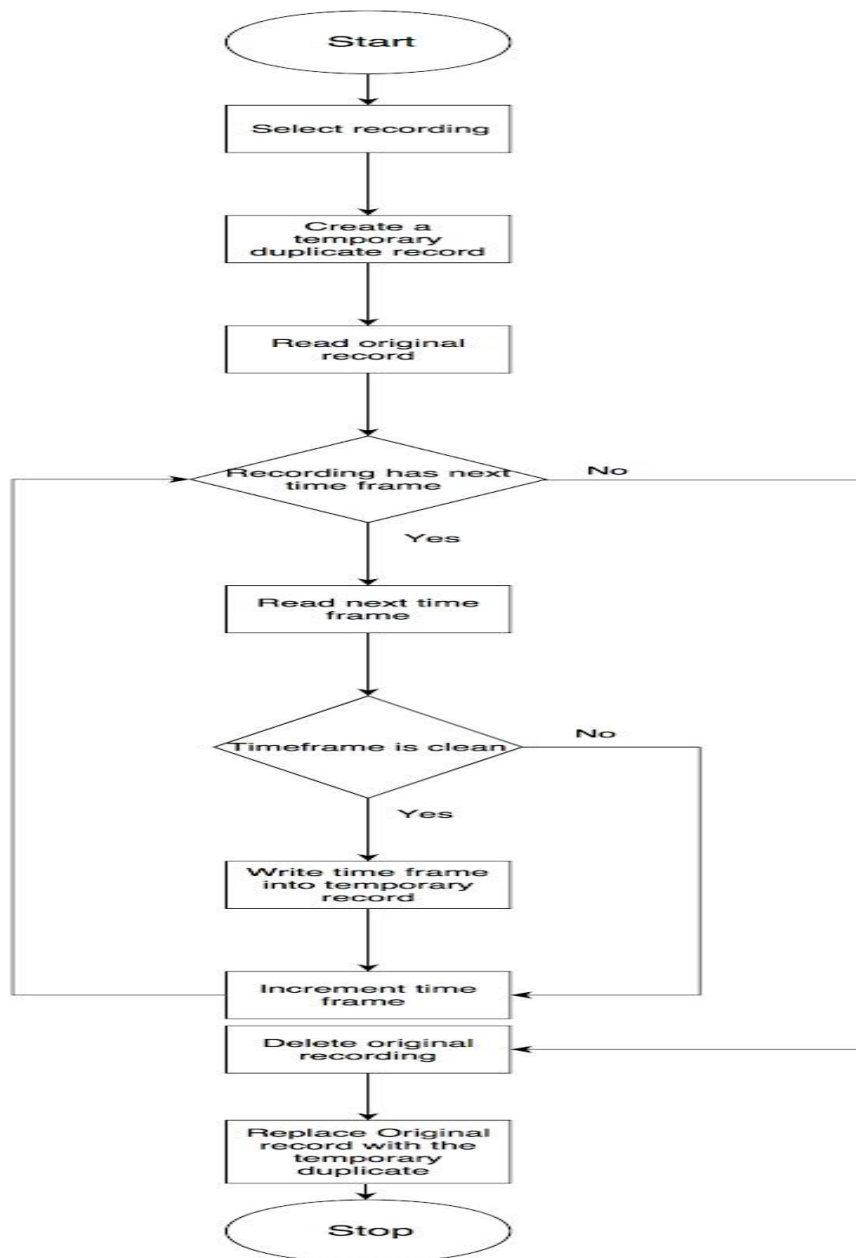
COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX I



Flow chart for data cleaning

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