DISCRIMINATION OF HEART SOUNDS USING CHOAS ANALYSIS IN VARIOUS SUBBANDS

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Abstract: Discrimination among different types of heart sounds has a significant impact in designing pHealth systems based upon this bio-signal, since (i) it enables the optimal selection and tuning of the analysis algorithms and (ii) it may be applied as a first level strategy for heart dysfunction diagnosis. In this paper we introduce an algorithm for heart sound type discrimination into three classes: healthy heart sounds, heart sounds with murmur produced by native heart valves and heart sounds produced by prosthetic mechanical heart valves. The algorithm is based on a nonlinear dynamical model of phase space reconstruction for various frequency bands. For each frequency sub-band the chaotic nature and the complexity of the signal is assessed using the largest Lyapunov exponents (LLE) and the correlation dimension (CD). The effectiveness of the method has been tested with heart sounds of 45 subjects (15 subjects of each class). It was concluded that LLEs and the CDs exhibit complementary significance in the discrimination among different classes of heart sounds.

1 INTRODUCTION

Auscultation has been a popular technique to examine the mechanical status of the heart. Its capacity to assess the cardiac mechanical state is comparable to the electrocardiogram in assessing the cardiac electrical state. It has been proven to be a noninvasive, inexpensive and effective method for the early detection of many cardiac disorders (Xiao et al., 2002), such as prosthetic and native heart valve disorder diagnosis and heart failure decompensation assessment. Besides these more conventional diagnosis functions, heart sounds may be applied for assessing several important cardiac reserve parameters for long-term patient surveillance. For instance, heart sounds may be applied as the source signal to estimate surrogate measures of continuous blood pressure, cardiac output and heart contractility as well as to measure the systolic heart time intervals. Due to its non-invasive and low intrusive nature it is an interesting bio-signal for designing systems to support pHealth applications for continuous and long-term use in several types of coronary and heart disease management tasks.

Heart sound signals are significantly more complex compared to other bio-signals such as the ECG or PPG. Their main sources of origin are the movements of the atrio-ventricular valves. However, other more subtle phenomena such as blood turbulence and heart wall vibration may contribute to the heart sound signal. These phenomena are highly correlated to specific heart dysfunctions and diseases and hence it is fundamental to design appropriate analysis algorithms that are able to adequately identify and extract these diagnosis features. A typical heart sound analysis algorithm pipeline encompasses several stages related to non-cardiac sound detection and removal, heart sound segmentation, diagnostic feature extraction and classification (see Figure 1). The degree of complexity and tuning of the required algorithms in each stage varies considerably according to the characteristics of the underlying heart sound. For instance, the segmentation of a heart sounds with systolic or diastolic murmur is considerably more complex and computationally expensive compared to the segmentation of a heart sound without murmur (see, for instance (Kumar et al., 2006a)(Kumar et al., 2006b)). On the other hand, some of the analysis stages are only required if some specific disease is known (or at least suspected) to exist. These issues are central in designing systems for personnel Health (pHealth) applications, where low power electronics

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are a typical design constraint and therefore limit the amount of computation that is available. For these reasons, it is observed that the discrimination among different types of heart sounds has a significant impact in designing pHealth systems, since it enables the optimal selection and tuning of the analysis algorithms and (ii) it may be applied as a first level of heart dysfunction diagnosis strategy. In this paper we introduce an algorithm for heart sound type discrimination into three types of classes: healthy heart sounds, heart sounds with murmur produced by native heart valves and heart sounds produced by prosthetic mechanical heart valves (see Figure 1).

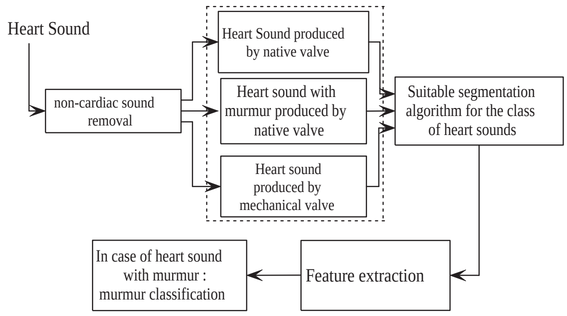

Figure 1: Main blocks for heart sound analysis framework where blocks under dotted square is for discrimination for the three groups of sounds.

In the best knowledge of the authors, no work has been proposed thus far that has attempted to solve the addressed problem in this paper. However, heart sounds with murmurs classification and heart sounds produced by mechanical valve have been separately investigated in the literature. Nevertheless, heart murmur classification provides insights for the addressed problem. Heart murmur segmentation and its recognition involves feature extraction and classification. Some of the recent works on heart murmur classification are based upon decision tree methods (Pavlopoulos et al., 2004), nonlinear dynamic methods using recurrent statistic analysis (Ahlstrom et al., 2006) and using features from nonlinear dynamical system (chaos and correlation dimension) analysis (Delgado et al., 2007).

This paper presents chaos and complexity measurement in different frequency bands of heart sounds in order to achieve the best distinction among three classes of heart sounds. Considering the range of frequency spectrum in each group, the signals are decomposed into 6 successive signals in decreasing frequency bands based on the wavelet decomposition technique. For each band, the phase space is reconstructed using one of the nonlinear times series methods, i.e. time delay embedding method. The chaos and complexity features are measured in the form of the largest Lyapunov exponents (LLE) and the correlation dimension (CD). Consequently, statistical analysis is performed to test the features' potential in distinction of these three groups of heart sounds.

The paper is structured as follows: section 2 presents a brief introduction of the applied method using phase space features, Lyapunov exponents and correlation dimension is presented. Section 3 contains the details of the method. In section 4 the achieved results using the test database composed by heart sounds of 45 subjects are presented and discussed. Finally, in section 4 some main conclusions and future working directions are outlined.

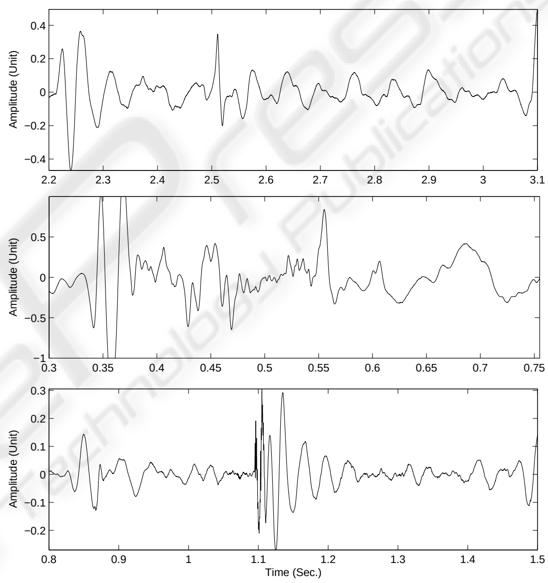

Figure 2: Three classes of heart sounds: a) Heart sound without any known cardiac disorder. b) Heart sound with systolic murmur, c) Heart sound collected from a heart with a mechanical valve implant.

2 METHOD

The proposed method for the discrimination between different classes of heart sounds is composed by three main steps, as it is summarized in Figure 3: 1) signal decomposition into different subbands using the wavelet transform technique, 2) chaos and complexity feature extraction using the nonlinear dynamic approach of phase reconstruction and 3) relevance assessment of the results using statistical analysis. Wavelet decomposition is chosen to decompose heart sound signal over the traditional Fourier transform based band-pass filter bank due to its advantage of time-frequency localization, multirate filtering and scale-space analysis. For computational efficiency the discrete wavelet transform with dyadic scales and translations is chosen. Mathematical background of the technique is out of the scope of the paper. However, an introductory explanation of nonlinear dynamical systems features is provided in this section, which will be further applied on the original as well as on the decomposed signals.

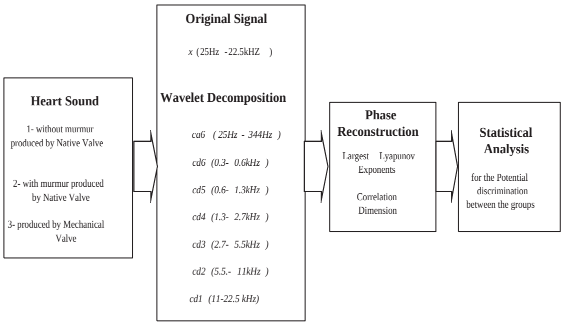

Figure 3: Workflow for the chaos analysis in the three groups of heart sounds.

2.1 Phase Space Reconstruction

In order to see the structures in chaotic behavior of a dynamical system through the time series produced by itself, a method of attractor reconstruction is applied. Attractor is a distribution of points in the phase or the state space that is characterized by the density of points. Suppose the heart is considered as a nonlinear dynamical system which state space is given as

$$\mathbf{X} = [\mathbf{X_1}, \mathbf{X_2}, \mathbf{X_3}....., \mathbf{X_P}]^{\mathbf{T}}, \quad (1)$$

where $\mathbf{X}_i$ is the state of the system at discrete time i, that generates the N-point heart sound time series $\{x_1, x_2, ...x_N\}$. A method of delay is applied to reconstruct the attractor in the multidimensional space or embedding space P, i.e.

$$\mathbf{X_i} = [x_i, x_{i-\tau}, ..., x_{i+(m-1)\tau}] \in \mathbb{R}^m \quad (2)$$

where $i = 1, 2, 3...P$ and $\mathbf{X}_i$ are row vectors of the embedding matrix $\mathbf{X}$ of size $P \times m$. Application of an (m, τ) window to a time series of N data points results in a sequence of $P = N - (m-1)$ vectors. In the phase space reconstruction, it is important that the two integer parameters (m, τ) are suitably estimated. The τ parameter is estimated as the time lag where the first minimum occurs in the mutual information between data vector $\{x_1, x_2, ...x_N\}$ and time lagged data vector $\mathbf{X_i}$. Using the estimated τ, the embedded matrix dimension m is estimated by utilizing Cao's method (Cao, 1997). The method exhibits invariance with respect to the data length (Cao, 1997). An example of reconstructed phase space using in murmur include heart sound is shown in Figure 4.

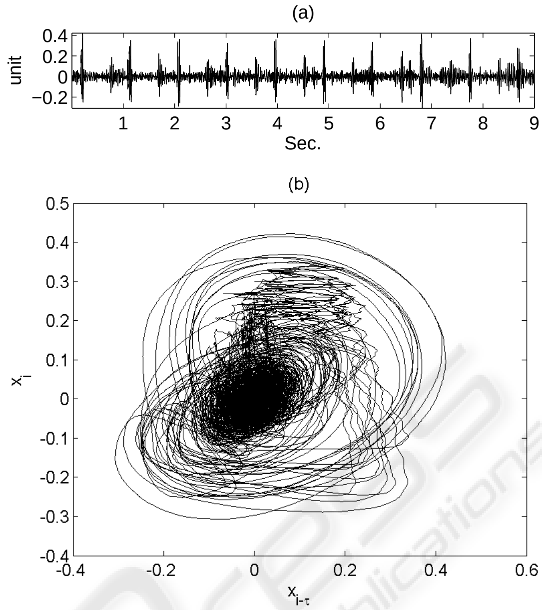

Figure 4: (a) A heart sound signal with murmur. (b) Reconstructed phase space with $\tau = 195$ and embedding dimension $m = 4$.

In order to know the attractor's behaviors in the phase space, two significant incidents can be observed: the first one is the rate of divergence or convergence of the trajectories and the second one is the geometry of the attractor. These can be quantified by the Lyapunov exponents and the correlation dimension. The fundamental reason of choosing Lyapunov exponents and correlation dimension for the time series characterization is to enhance the knowledge about the underlying system rather than simply compressing many measurements into a number. This can not be achieved by many statistics measurements. A quantity which can serve this objective must be independent of measurement procedure, coordinates chosen, noise, etc. According to their definition, correlation dimensions and Lyapunov exponents nearly fulfil these criteria.

2.2 Lyapunov Exponents

In a phase space plot, it is observed that the trajectories diverge over a course of time very slowly in periodic time series. Chaos is thought to be present only if divergence is exponentially fast. The averaged exponents of increase or decrease of separation quantifies the strength of chaos, which is known as the Lyapunov exponents (Kantz and Schreiber, 1997). One of the most robust and computationally fast methods is the one introduced by Rosentein (Rosenstein et al., 1993) is adopted.

There are many Lyapunov exponents for the attractor, only the largest is computed that is significant to represent the level of chaos in heart sound signals. The largest Lyapunov exponent (LLE) may have negative, positive or zero value. Time series from a dissipative system may yield LLE negative values, while marginally stable systems zero LLE. Positive value of LLE denotes chaos in the system.

2.3 Correlation Dimension

Correlation dimension is a measure of self-similarity (geometry of the attractor) in the time series. This quantity is computed through correlation sum $C(r)$, that is a fraction of all possible pairs of points which are closer than a given radial distance r in a particular norm. The sum counts the pair whose distance is smaller than r. Since at large number of points correlation sum follows power law, correlation dimension can be defined with the logarithmic change in correlation sum with respect to the logarithm of the distance r. More mathematical explanation can be found in (Kantz and Schreiber, 1997).

3 APPLICATION AND RESULTS

3.1 Data Collection

Heart sounds containing murmurs produced by native heart valve as well as heart sounds produced by heart with a mechanical valve implant, were collected from the Cardiothoracic Surgery Center of the University Hospital of Coimbra. Heart sounds produced by mechanical valves were recorded 2-3 weeks after valve surgery and do not exhibit murmurs. Some heart sound samples of healthy subjects (who did not have any kind of CVD) were collected from researchers at the University of Coimbra and Philips Research Laboratories. For this purpose, a quiet location was chosen where subjects were asked to avoid movements during measurements. In most cases, the supine position was adopted as the best auscultation position for the subjects and the best auscultation site (near to the second or the third intercostal space) was selected based on the loudness of the heart sounds. The prepared database was categorized into the three groups: group H; heart sounds produced by native valve, group M; heart sounds with murmur produced by native valves, and group V; heart sounds produced by mechanical valve.

Data acquisition was performed with an electronic stethoscope from Meditron. The stethoscope presents excellent signal to noise ratio characteristic and an extended frequency range (20 - 20,000 Hz). The normal amplitude can be regulated up to a maximum of 93 dB. Sound samples can be sampled up to a maximum sampling rate of 44.1kHz and digitized with a 16-bit ADC. All collected heart sound samples were sampled at the rate of 44.1kHz for at most one minute. Later, only 9 seconds length of heart sounds of each subject is applied for the discrimination test.

3.2 Pre-processing and Wavelet Decomposition

All collected heart sounds are first preprocessed using a 4th order Butterworth high pass filter with a cut-off frequency of 25Hz in order to eliminate low frequencies produced by muscle and stethoscope movements.

The resultant heart sounds are decomposed into seven frequency bands with the range of 25Hz-22.5kHz. It should be noticed that various frequency bands are present in heart sounds produced by native or mechanical valve. For instance, mechanical valve produces frequency up to 50kHz (Zhang et al., 1998), whereas the heart sounds produced by native valves, even with murmurs, fall into a frequency range of 25Hz-600Hz (Erickson, 2003).

As it has already been mentioned, the heart sounds are decomposed using the wavelet decomposition technique. Given the Daubechies wavelet's properties related to the suppression of the instrumental defects (i.e. *polynomial components*) and the absence of the Gibbs phenomenon (no ripple in frequency response) (Strang and Nguyen, 1996), it is chosen to correlate with the heart sound signals.

The heart sound signals are subjected to 6 decomposition level using 6^{th}- order Daubechies wavelet transform. The band limited (25Hz-22.5kHz) heart sounds, x, are decomposed into two frequency bands signals: $ca1$ that contains frequency bands (25Hz-11.025kHz), and $cd1$ (11.025-22.5kHz). The $ca1$ is further decomposed into band limited signals $ca2$ (25Hz-5.5kHz) and $cd2$ (5.5-11kHz). The approach is repeated until four following frequency band signals : $cd3$ (2.7-5.5kHz), $cd4$ (1.3-2.7kHz), $cd5$ (0.6-1.3kHz), $cd6$ (0.3-0.6kHz) and $ca6$ (25-344Hz), as can be seen in Figure 5. The subbands signals $ca6, cd6, cd5, cd4, cd3, cd2$ and $cd1$ reconstruct the original signal. The differences in the subbands exhibit physiological significance. For instance, heart sounds produced by healthy hearts should have their energy concentrated mainly in $ca6$ band, while heart sounds with murmur typically exhibits a significant amount of energy in the $cd6$ or even in $cd5$ band. Heart sounds produced by prosthetic mechanical heart valve usually exhibit high frequency contents.

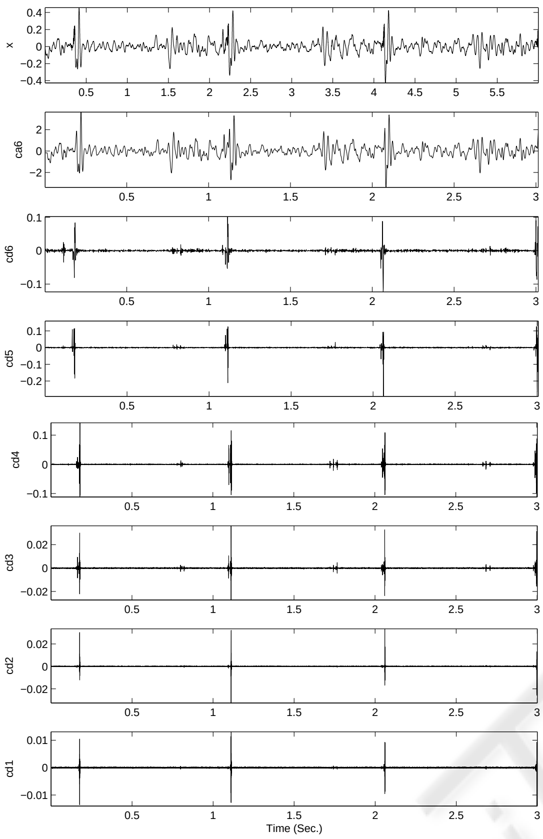

Figure 5: Level 6 decomposition of a Heart sound with murmur sound samples using Daubechies 6^{th} order (where, $x = ca6 + \sum_{k=1}^{6} cd_k$).

3.3 Attractor Reconstruction and Chaotic Features Computation

The required parameters for the attractor reconstruction (τ, m) are estimated for each heart sound in each group. The time delay parameter, τ, is computed as the first local minimum in the plot of the mutual information. The embedding dimension is obtained using the well known Cao's method (Cao, 1997).

The Lyapunov exponents are computed based on well known Wolf's (Rosenstein et al., 1993) method. The single largest Lyapunov exponent (LLE) of the heart sound is computed using least square fit in the plot of logarithm of divergence over increasing time steps, as depicted in Figure (6). The slope of the line fitted to the data is computed as the largest Lyapunov exponent.

In the correlation dimension computation, the only crucial variable is the radial distance (r) for the identification of the number of neighbors of the reference point. In case of a very small radius not enough points are captured. On the other hand, in case of a large value, most of the available points are captured. Both situations mislead the correlation dimension computation. Care must be taken in choosing the value, which led to experiment with range of r, i.e. 5%-25% of the attractor size. This range of radius enables the fair estimate values of CD, which do not predominantly vary from each other. In our implementation, we have chosen experimentally a 8% distance value (r) for further statistical analysis. The CD is nothing but a slope of the line which can be approximately fit with the logarithm of correlation sum ($C(r)$). In the Figure 6(b), the CD is computed using the plot of correlation sum over distance.

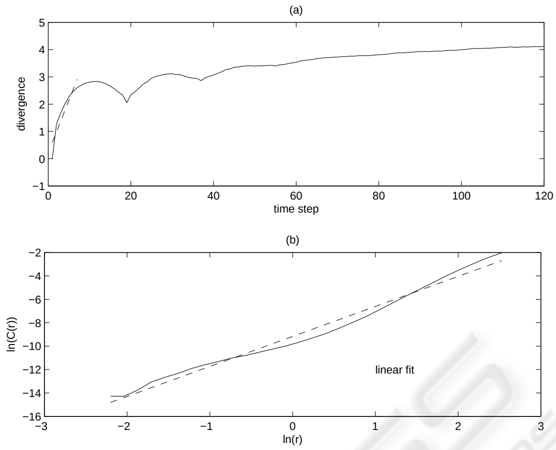

Figure 6: Embedding features computation by linear least square fitting : (a) Largest Lyapunov exponent (b) Correlation dimension.

3.4 Statistical Analysis

The computation of the features based on the embedded matrix of the heart sound samples have been presented in the previous section. It has been applied to all the 45 data samples of the three groups, where each group contains 15 heart sound samples from different subjects. The average value of LLE and CD of the original and decomposed signal are listed in Table 1. The values are not monotonically increasing or decreasing in the descending frequency subbands in either of these groups. Instead, some values are nearly overlapping among the groups. Therefore, there is a risk to apply a hard threshold to these measures in distinction between the groups.

From the LLE values in Table 1, it can be observed that the original heart sound signals and the subband signals of each group differ significantly. The LLE of the original signal of the group V (0.123) is significantly higher than those of group M (0.073) and group H (0.073). The values are found to be lower for subband $cd1$ and $cd2$ in group V (0.233 and 0.249) than in group H (0.042 and 0.073), though the difference is not considerably high, whereas in the other subbands the values are higher in group V than in group M and H. Hence, it can be deduced that heart sounds of group V is more chaotic in nature than the other groups in the original band signal and the subbands $ca6, cd6, cd4,$ and $cd3$. That can be explained based upon the single-tilting disk mechanical valve closing which produces a vast frequency range (up to 50kHz) of sound. However, it is more chaotic than the group H but less than the group M in the subbands $cd2$ and $cd1$. The most interesting observation is to find that the values of the group M higher than those of group H in all subbands. The attractor of the healthy heart sound is less chaotic compared to the attractors obtained from heart sounds produced by hearts with disorders.

Table 1: Averaged Largest Lyapunov Exponents (LLE) values for all three data groups. Standard deviations are in parenthesis.

Signal	Group H	Group M	Group V
x	0.042 (0.018)	0.073 (0.048)	0.123 (0.049)
$ca6$	0.215 (0.080)	0.246 (0.115)	0.308 (0.116)
$cd6$	0.279 (0.100)	0.331 (0.139)	0.489 (0.132)
$cd5$	0.236 (0.101)	0.269 (0.141)	0.431 (0.207)
$cd4$	0.178 (0.110)	0.259 (0.134)	0.366 (0.111)
$cd3$	0.170 (0.071)	0.249 (0.065)	0.305 (0.067)
$cd2$	0.242 (0.117)	0.304 (0.198)	0.249 (0.094)
$cd1$	0.222 (0.059)	0.302 (0.189)	0.233 (0.126)

From the CD values in Table 2, it can be observed that the original band limited heart sounds, x, of all the groups do not exhibits considerable difference among each other. This implies that the complexity in nonlinear dynamics of the attractors is almost the same for all heart sounds. The subbands $ca6, cd6, cd5, cd4$ and $cd3$ yield almost similar values of CD in each group. The values suggest moderate variation in complexity of the groups in these subbands. However, in subband $cd2$, the group V (4.18) appears to be significantly higher compare to the group H (3.66) and reasonably above the value of group M (3.97). Furthermore, subband $cd1$ also yields a larger value of CD for the group V (4.43) than for group M and H. It indicates increased complexity of the group V, which may be used in the discrimination of the group.

In the further discussion about the yielded values of LLE, a significance analysis is performed using one-way variance analysis (ANOVA) with 99% confidence level. Let α be the confidence level at which the null hypothesis (similar averaged value groups) can be rejected, variance in the values of LLE and CD is searched greater to 99% (α = 0.01) when F-statistic is below 0.001. The achieved results exhibit the same results as it has already been presented in Table 1. It can be seen in Figure 7(a) that LLE of the original sounds of group H, group M and group V can be discriminated from the original heart sounds (F=0.0006689). However, band $cd3$ ($F = 0.0000952$) has better potential to discriminate all the three groups from each other, see Figure 7(b). The $cd2$ is able to distinct group V from group H and group M.

Table 2: Averaged Correlation Dimension (CD) values for all three data groups using 8% distance of the attractor for neighbor search from the reference point. Standard deviations are in parenthesis.

Signal	Group H	Group M	Group V
x	4.25 (0.44)	3.88 (0.21)	4.12 (0.23)
$ca6$	3.94 (0.36)	3.65 (0.65)	3.89 (0.31)
$cd6$	3.70 (0.27)	3.46 (0.42)	3.80 (0.32)
$cd5$	3.63 (0.64)	3.58 (0.49)	3.60 (0.36)
$cd4$	3.68 (0.66)	3.87 (1.19)	3.75 (0.31)
$cd3$	3.72 (0.81)	3.95 (0.72)	3.89 (0.60)
$cd2$	3.66 (0.88)	3.97 (0.88)	4.18 (0.62)
$cd1$	3.19 (0.73)	3.42 (0.92)	4.43 (0.59)

On the other hand, it can be seen in Figure 7(c) that the CD values of $cd6$ are able to discriminate group V from group H and M (F=0.0000952). Furthermore, CD values of $ca6$ are able to discriminate group M from group H and group V (F=0.00066896), see in Figure 7(d).

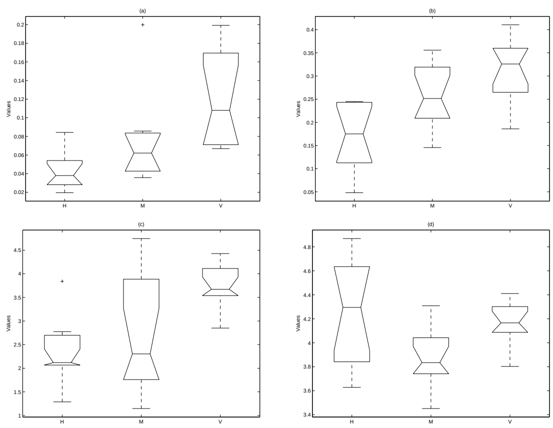

Figure 7: Confidence interval plots of LLE ((a) original heart sound, (b) $cd3$) and CD ((c) $cd6$, (d) $ca6$) value of in all the groups.

4 CONCLUSIONS AND FUTURE WORKS

Chaos and complexity analysis in seven frequency subbands ($ca6, cd6, cd5, cd4, cd3, cd2, cd1$) of three groups of heart sounds were computed in order to discriminate these groups of heart sounds. The three groups of heart sounds are heart sounds produced by native valve, heart sounds with murmur produced by native valve and heart sounds produced by mechanical valves. These are compared with respect to their degree of chaos which was quantified as largest Lyapunov exponents (LLE) as well as complexity in the form of the correlation dimension (CD). These quantities were computed for seven frequency bands, which were achieved by applying a wavelet decomposition. Then statistical analysis was performed to test the method's effectiveness. The LLE values of subband $cd3$ is found to be the best for group discrimination from each other and CD values of subband $ca6$ are found to be the best signals to discriminate heart sound with murmur produced by native valves from the rest of the two groups.

The decomposition of the original heart sound into seven subbands alters the original phase space, and exhibit different chaotic and complex behaviors. Observing the results, one may conclude that only LLE can discriminate among the three groups of heart sounds. However, it is observed that CD can be used to discriminate one group of heart sound from the rest of the two groups in the specific bands with greater confidence level. Therefore, it can be concluded that heart dynamics are not spread out equally across the spectrum of heart sounds, but instead, are limited to certain frequency band.

In the near future, work will include testing the method with large database as well as the fine tuning of the frequency bands for analysis.

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