Heart Murmur Classification using Complexity Signatures

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Abstract

Heart sounds entail crucial heart function information. In conditions of heart abnormalities, such as valve dysfunctions and rapid blood flow, additional sounds are heard in regular heart sounds (HS), which can be employed in pathology diagnosis. These additional sounds, or so-called murmurs, show different characteristics with respect to cardiovascular heart diseases, namely heart valve disorders. In this work, we propose a two-stage classifier based on the analysis of the heart sound's complexity for murmur identification and classification. The first stage of the classifier verifies if the HS exhibits murmurs. To this end, the chaotic nature of the signal is assessed using the Lyapunov exponents. The second stage of the method is devoted to the classification of the type of murmur. In opposition to current state of the art methods for murmur classification, a reduced set of features is proposed. This set includes both well-known as well as new features designed to capture the morphological and the chaotic nature of murmurs. The classification scheme is evaluated with three classification methods: Learning Vector Quantization (LVQ), Gaussian Mixture Models (GMM) and Support Vector Machines (SVM). The achieved results are comparable to reported results in literature, while relying on a significant smaller set of features.

1. Introduction

Auscultation is the preferred method for heart valve disorders diagnosis [3]. To develop medical decision support systems based on HS analysis, it is important to develop automatic analysis techniques, particularly segmentation of heart sound into its main components (i.e., S1, S2 and murmur) and their recognition. Heart murmur classification has been attempted with various pattern recognition methods. Ahlstrom et al. [1] propose a feed-forward neural network for the discrimination of systolic heart murmurs. The feature space suggested by these authors is composed by a total of 207 features, which are extracted using techniques such as Shannon energy, wavelets, fractal dimensions and recurrence quantification analysis. DeGroff et al. [2] suggest a three-layered neural network based classification scheme to distinguish between innocent and pathological murmurs in children. These authors use the normalized energy spectrum of the heart sound, with various spectral resolutions and frequency ranges, as input features. In [4] a dynamic grown and learn neural network is applied to classify heart sounds into normal, systolic murmur and diastolic murmur. Again a high dimension feature vector is employed resorting to Daubechies-2 wavelet detail coefficients at the second decomposition level. The reported classification accuracies of current state of the art murmur classification methods are in the range of 86% to 97%. It should be mentioned that the reported results are not directly comparable, since no common database was applied.

In this work, we propose a two-stage HS murmur classification scheme based on the analysis of the signal's complexity. The first stage of the classifier is intended for the verification of murmur existence in a HS. In order to achieve this task, the signal is transformed into a phase space representation that is reconstructed using the embedded matrix. The chaotic nature of the signal, assessed using the Lyapunov exponents, is applied for murmur presence assessment. The second stage of the method is devoted to the classification of the type of murmur into seven distinct classes with clinical significance. In opposition to current state of the art methods for murmur classification, a reduced and physiolog-

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ically meaningful set of features is proposed. This set includes both well-known as well as new features designed to capture the morphological and chaotic nature of murmurs. Regarding the well-known features, it should be mentioned that many of them are usually not employed in the context of murmur classification. Finally, the classification scheme is evaluated with three distinct classification methods: Learning Vector Quantization (LVQ), Gaussian Mixture Models (GMM) and Support Vector Machines (SVM). This approach builds on top of a robust HS segmentation method that has been recently introduced by the team [7][6].

In section 2, the two-level HS murmur classification scheme is thoroughly described. The achieved results using aforementioned classifiers are then analyzed and discussed in Section 3. Finally, in Section 4, conclusions are drawn and possible future directions are pointed out.

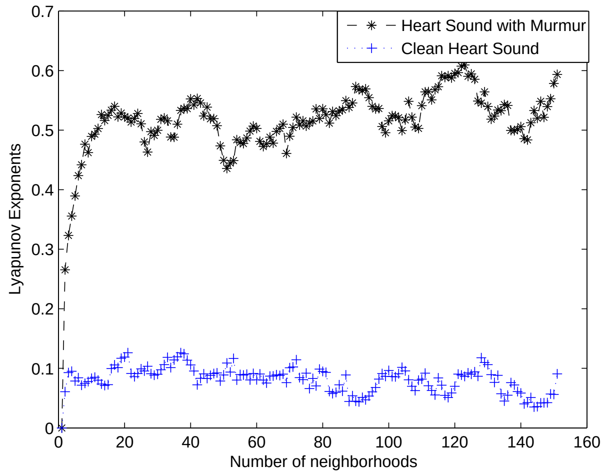

Figure 1. Average Lyapunov Exponents of 20 clean heart sounds and 15 murmur with length of 88200 samples.

2 Method

The first step in the process of heart murmur classification is to detect the systolic and diastolic regions of the heart cycle. The boundaries of murmurs are complimentary to the boundaries of S1 and S2 sound components, which correspond respectively to the closing of the atrio-ventricular valves and the aortic/pulmonary valves. Therefore, finding S1 and S2's boundaries renders the starting and stopping points of the murmurs. In previous works [7][6], we have introduced a robust HS segmentation method. The subsequent task is to i) evaluate if the HS sample exhibits murmurs and ii) to classify their origin. In the proposed approach these two problems are tackled using two sequential classifiers based on the chaos assessment of the signal under analysis.

2.1 Murmur identification

Suppose the heart is considered as a nonlinear dynamical system $X(t+1) = F[X(t)]$ that generates the heart sound time series $x(t), t = 1....N$. Signal $x(t)$ can be treated as a one dimensional projection of the unknown multidimensional dynamic variable $X(t)$. Phase space transformation of the one dimensional observation $x(t)$ is performed using the embedding theorem [6]. The method of delay is applied to reconstruct the attractor in the multidimensional space or embedding space P, i.e. $y_i(t) = [x(t), x(t-\tau), ..., x(t-(m-1)\tau))] \in \mathbb{R}^m$, where $i = 1, 2, 3...P$ and $y_i(t)$ are row vectors of the embedding matrix $Y(t)$. The τ parameter is estimated as the time lag where the first minimum occurs in the mutual information between data vector $x(t)$ and $x(t-\tau)$. Using the estimated τ, the embedded matrix dimension m is estimated by utilizing Cao's method [5].

The trajectories in the reconstructed phase space are related to the chaotic natures of a dynamical system and might be assessed using the Lyapunov exponent. These reveal how the orbits on the attractor move apart (or together) under the evolution of the dynamics [6]. To determine the exponents from the embedded matrix, the nearest neighbor points are located to measure their distance from $y_i(t0) = [x(t0), x(t0-\tau), ..., x(t0-(m-1)\tau))$. Let $L(t0)$ be the distance between neighbor points and the initial points. To quantify this distance, it is assumed that the rate of growth (or decay) of the separation between the trajectories is exponential in time. Furthermore, it is also assumed that at time t1, the initial length expands or shrinks to $L'(t1)$. The average of exponential rate of divergence of close orbits is characterized by (1), where M is the number of repetitions the trajectory takes in traversing the entire data and denotes the Lyapunov exponents. The average of 150 exponents are plotted over a number of neighborhoods in figure 1.

$$\lambda = \frac{1}{(t_M - t_0)} \sum_{k=1}^{M} log_2 \frac{L'(t_k)}{L'(t_{k-1})}, \quad (1)$$

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Let λ_{test} be the Lyapunov exponents of the test heart sound signal, and let λ_{HsMav} and λ_{Hsav} be the expected Lyapunov exponents of heart sounds, respectively with and without murmur. Classification is performed according to the threshold process defined in (2).

$$Heart\ Murmur = \begin{cases} Yes & \parallel \lambda^{test} - \lambda_{av}^{HsM} \parallel < th \\ No & otherwise \end{cases}, \quad (2)$$

2.2 Murmur classification

Accurate murmur classification demands acquisition of meaningful, discriminative, features. Such features can be categorized into several classes, e.g., timing, shape, location, radiation, intensity, pitch and quality or timbre. In this work, features are grouped in 3 classes: time domain, frequency-domain and statistical features.

2.2.1 Time-domain features:

Time domain features (5 features) are extracted from the original murmur segment, i.e. without performing any temporal transform. Some features, such as timing, intensity, frequency location over time and shape, are computed in the time domain. These characteristics are obtained by computing duration, loudness, and jitters [7][8]. Besides these features zero crossing rate and a new features, transition ratio, are also included.

Zero crossing rate (zcr): It is related to the density occurrence of samples over time, and known to be a descriptor of frequency and timbre, computed as in (3).

$$zcr = \frac{1}{n^i - n^e} \sum_{j=n^i}^{n^e} |sgn(x(j)) - sgn(x(j-1))|, \quad (3)$$

where n^i and n^e are starting point and stoping point sample, respectively.

Transition ratio: It is a new feature to know the morphology of the segments. It is computed in a form of the ratio between two times measures as in (4).

$$transition\ ratio = \frac{T_{asc}}{T_{dsc}}, \quad (4)$$

where T_{asc} is the transition time taken from the first minimum energy, in $x(t)^2$, to the maximum energy, and T_{dsc} one is from the maximum to the second minimum energy.

2.2.2 Frequency domain features:

Frequency-domain features capture characteristics of the signal's timbre and morphology. In order to compute those features, the power spectrum of the signal is computing resorting to the periodogram. 10 frequency-domain features are extracted, as explained below.

Spectral power: Spectral power is computed through periodogram via summation over frequency. Since the power of murmurs spreads across various frequency regions (0-400Hz). Therefore, to examine the dominance of spectral power at specific frequencies, spectral power is computed in four frequency bands: 0-0.1kHz; 0.1-0.2kHz, 0.2-0.3kHz, and 0.3-0.4kHz. Hence, 4 features as the powers in four bands are computed by summing over frequency.

Spectral power based features: From the basis of the above power spectrum following features are carried out which mainly provides murmur's morphology, shapes and fundamental frequencies: centroid, flux, skewness, kurtosis for shape and morphologies. While, spectral peaks are the dominant frequencies [8].

2.2.3 Statistical domain features:

The distribution and scattering of samples in the murmur is observed in using histograms and phase space. The following features (3 features) are computed:

Skewness and Kurtosis: Two measures, skewness and kurtosis, are computed through the histogram of the heart murmur segment.

Chaos: The maximum of Lyapunov exponents, from (1), is taken as the quantifier of the degree of chaos in the murmur segments.

3 Results and Discussions

Heart sounds containing murmurs were collected from the Cardiothoracic Surgery Center of the University Hospital of Coimbra. 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). Sound samples were recorded for the maximum duration of one minute,

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using a 16-bit ADC at 44.1kHz sampling rate. Total 15 normal heart sound, and 51 heart sound with murmur signals which corresponding to 2047 beats, were collected.

As described previously, a two-stage hierarchical classification approach was carried out. The one second length of heart sound is taken to assess as HS, or HS with murmur. In the first stage, clean and murmur sounds are separated. In the prepared database, at this stage, sensitivity and specificity of 100% are achieved.

In the second classification stage, sounds classified as murmur are further categorized into the following 7 classes: 1) Aortic Regurgitation (AR), 2) Aortic Stenosis (AS), 3) Mitral Regurgitation (MR), 4) Pulmonary Regurgitation (PR), 5) Pulmonary Stenosis (PS), 6) Subaortic Stenosis + Ventricular Septal Defect (SAS+VSD), 7) Systolic Ejection (SE). Here, clean sounds incorrectly classified as murmur sounds in the first stage will be assigned to one of the seven defined categories.

Three classification methodologies (LVQ, GMM and SVM) were employed. In LVQ and GMM, the classifiers were trained with 70% of the whole dataset, whereas SVM used 50%.

Table 1. Performance in terms of sensitivity (SE) and specificity (SP) the classifiers.

Murmur Class	Sensitivity (%)			Specificity (%)		
	LVQ	GMM	SVM	LVQ	GMM	SVM
AS	89.36	90.84	89.67	82	95.11	94.31
AR	79.24	93.21	91.59	80.78	98.10	90.23
MR	74.23	95.81	93.58	74.87	91.24	89.92
PR	62.23	91.56	95.54	77.86	89.57	91.88
PS	100	89	100	87.43	100	100
SAS+VSD	81.34	91.89	93.23	76.55	86.33	91.23
SE	84	92.50	98	83	100	100
Overall	81.48	91.83	93.65	80.35	94.33	93.93

The results achieved are shown in the Table 1 in the form of classification sensitivity (SE) and specificity (SP), respectively. From the table it can be observed that the overall performance of GMM and SVM is nearly similar. Regarding sensitivity, GMM outperformed SVM in the AR and MR classes, whereas the reverse occurred in the PR, PS and SE categories. As for specificity, both algorithms performed similarly in most classes, except for AR, where GMM stood out, and SAS+VSD, where SVM was better.

4 Conclusions

A two-stage classifier based on the analysis of the heart sounds complexity for murmur identification and classification was introduced. The first stage of the classifier verifies if the HS exhibits murmurs. To this end, the chaotic nature of the signal is assessed using the Lyapunov exponents. The second stage of the method is devoted to the classification of the type of murmur. For this purpose, a set of well-known and some new features designed to capture the morphological and the chaotic nature of murmurs. The classification scheme is evaluated with three classification methods: Learning Vector Quantization (LVQ), Gaussian Mixture Models (GMM) and Support Vector Machines (SVM). While using reduced featurs data set, the results are significant and comparable to the past works.

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References

[1] C. Ahlstrom, P. Hult, P. Rask, J. Karlsson, E. Nylander, U. Dahlstro, and P. Ask. Feature extraction for systolic heart murmur classification. *Annals of Biomed. Engg.*, 34(11):1666–1677, 2006.

[2] C. G. DeGroff, S. Bhatikar, J. Hertzberg, R. Shandas, L. Valdes-Cruz, and R. L. Mahajan. Artificial neural network-based method of screening heart murmurs in children. *Circulation*, 103:2711–2716, 2001.

[3] B. Erickson. *Heart Sound And Murmurs: Across the Lifespan.* Mosby, inc. edition, 2003.

[4] C. N. Gupta, R. Palaniappanb, S. Swaminathan, and S. M. Krishnan. Neural network classification of homomorphic segmented heart sounds. *J. of applied soft computing*, 7:286–297, 2005.

[5] H. Kantz and T. Schreiber. *Nonlinear Time Series Analysis.* Cambridge university press edition, 1997.

[6] D. Kumar, P. Carvalho, M. Antunes, J. Henriques, A. Sá e Melo, and J. Habetha. In *Heart Murmur Recognition and Segmentation by Complexity Signatures*, pages 2128 – 2132. An. Int. IEEE EMBS Conference, 2008.

[7] D. Kumar, P. Carvalho, M. Auntunes, J. Henriques, M. Maldonado, R. Schmidt, and J. Habetha. In *Wavelet Transform And Simplicity Based Heart Murmur Segmentation*, pages 173–176. IEEE Computers in Cardiology, 2006.

[8] G. Tzanetakis and C. Perry. Musical genre classification of audio signals. *IEEE Tran. on Speech And Audio Processing*, 10(5):293–302, 2002.