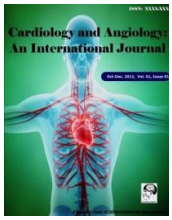

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Signal Processing Tools for Heart Sounds Analysis Based on Time-Frequency Domain

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Authors' contributions

This work was carried out in collaboration between all authors. Author AM designed the study, wrote the protocol, and wrote the first draft of the manuscript. Authors AM, CB, AD managed the literature searches, analyses of the results of the study. All authors read and approved the final manuscript.

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ABSTRACT

This paper present several signal processing tools for the analysis of heart sounds. Cardiac auscultation is noninvasive, low-cost and accurate to diagnose some heart diseases. A new module for the segmentation of heart sounds based on S-Transform is presented. The heart sound segmentation process divides the Phono Cardio Gram (PCG) signal into four parts: S1 (first heart sound), systole, S2 (second heart sound) and diastole. The segmentation can be considered one of the most important phases in the auto-analysis of PCG signals. A segmentation method based on the Shannon energy of the local spectrum calculated by the S-transform is proposed. Then, the energy concentration of the S-transform is optimized to accurately detect the boundaries of the localized sounds. New features based on the energy concentration of the S-transform are

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proposed to classify S1 and S2 and other features based on the complexity measure via Time-Frequency (TF) domain are proposed to detect systolic murmurs.

Keywords: Heart sounds; segmentation; feature extraction; classification.

1. INTRODUCTION

The recent advances in signal processing lead to powerful applications in the real life conditions for Doctors and medical staff.

Simultaneous technological evolutions with the development of non connected devices allow new approaches for medical practice via telemedicine.

Combination of the two developments lead to an increase in clinical diagnostic power immediately if signal processing is available on an hosting device or after connection to a reference center.

Raw heart auscultation data have to be converted in a phonocardiogram.PCG can be associated or not to simultaneous registrations of blood pressure, SAO2 or ECG by example.

As well single heart auscultation treated as a PCG includes enough information to authorize segmentation of the heart cycle.

Therefore heart rate, duration of systole and diastole detection of pathologic events can be easily detected.

The focus of this paper is the PCG signal (Fig. 1) obtained from auscultation, first medical step in clinical examination, with an electronic stethoscope [1,2]. The PCG reveals the mechanical activity of the heart and it can be considered as non-stationary signal.

For an untrained human ear, it's not an evidence to localize heart sounds, recognize their internal components and classify the murmurs and their origins. For that, the signal processing tools allow better estimation and detection of these signals. In this respect, different approaches could be considered to improve the electronic stethoscope [3]:

- Tools providing embedded autonomous analysis, easy to use by the general public at home for auto-diagnosis, monitoring and warning if need be.
- Tools providing sophisticated analysis (coupled to a PC, Bluetooth link) for the use of professionals in order to make an in-depth medical diagnosis and to train medical students.

In the past twenty years, many studies have interested in the PCG signal processing field (see Fig. 2); for the de-noising of the PCG many advanced tools of signal processing are used as the Kalman filter [4], the wavelets, and more recently the Emperical Modal Decomposition (EMD). For the time-frequency representation of the PCG signal the famous STFT is used [5], the Continuous Wavelet Transform (CWT) [6], the S-transform [7] and the Wigner-Ville Distribution (WVD) [8,9] etc. For the segmentation process the methods can be classified depending on the domain on which they are applied: time domain (Shannon energy [10]), frequency domain (homomorphic filter [11], time-frequency domain (wavelet transform[12], S-transform [13]) and nonlinear domain (Radial basis function [14]). For the classification of heart sounds: Artificial Neural Networks (ANN) [15], K-Nearest Neighbors (KNN) [16] and Support Vector Machines (SVM) [17,18].

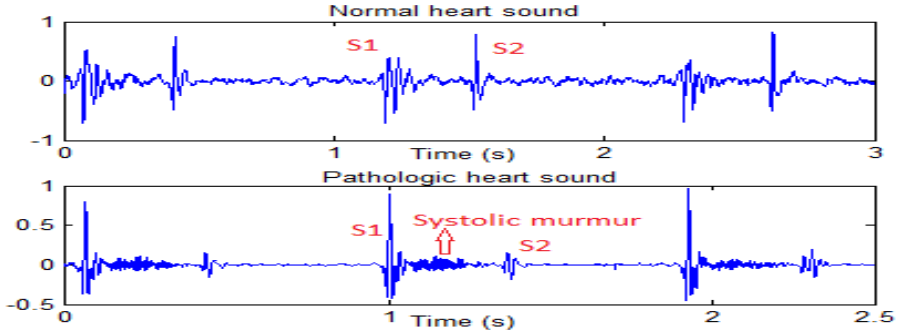

Fig. 1. Example of a normal (top) and pathologic (bottom) heart sounds with systolic murmur

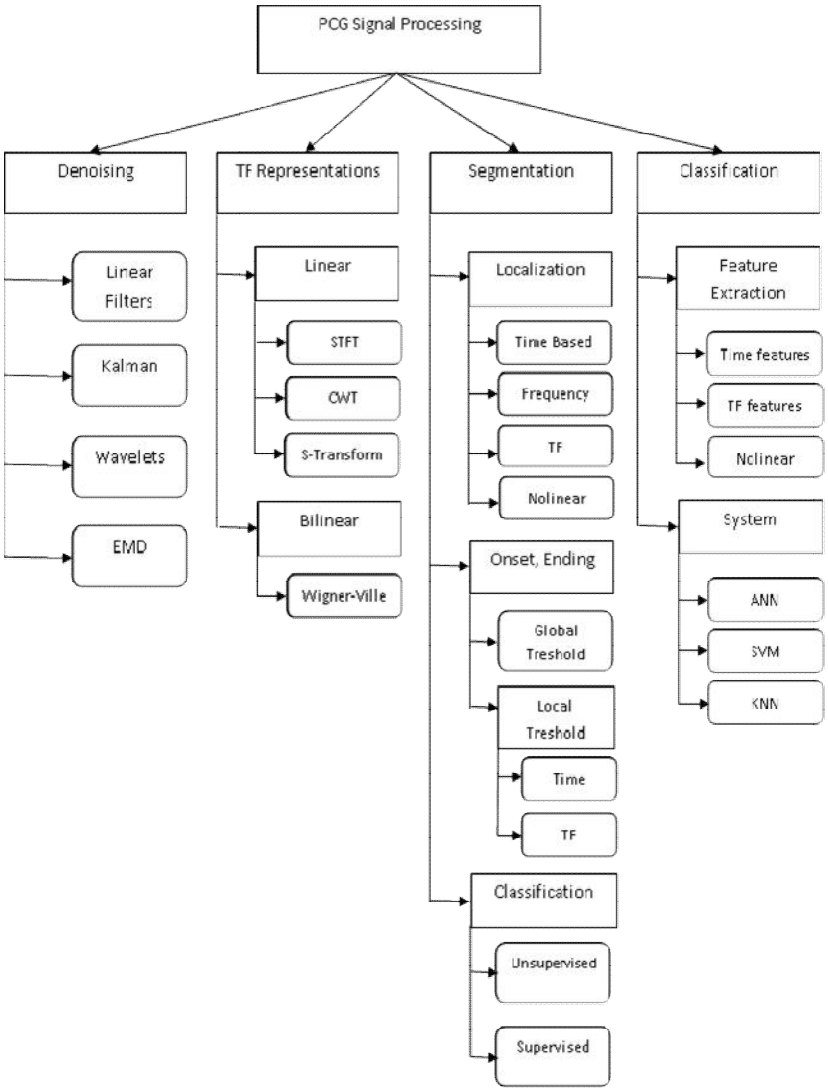

Fig. 2. An overview of the different contributions existing in the literature concerning the PCG signal processing algorithms and methods

The segmentation is one of the first phases of the heart sound analysis. Heart sound segmentation partitions the PCG signals into cardiac cycles and further into S1 (first heart sound), systole, S2 (second heart sound) and diastole [3]. Manypapers in the literature that tried to segment heart sounds without any help of ECG as Shannon energy [10], Hilbert Transform [19], high order statistics [20], a hidden Markov model [21], among others.

In this paper we present some signal processing tools based on time frequency domain to segment, classify and extract feature from heart sounds. The results are based on some real examples used as preliminary validation of the proposed methods.

2. METHODS AND MATERIALS

2.1 Sounds Collection

The heart sounds have been collected in the Hospital of Strasbourg (France) where Different cardiologists equipped with a prototype electronic stethoscope. The sounds are recorded with 16 bits accuracy and 8000Hz sampling frequency in a wave format. Recruitment was made through clinical research project (HUS-PRI 4179) with the support of the clinical investigation center

(INSERM) All of the participants have given a written informed consent. The best auscultation focus has been registered. Duration of registration varied from 8 to 12 s while patients controlled their respiration. Just some examples are included in this paper to perform a preliminary validation of the proposed methods.

2.2 Localization and Segmentation of Heart Sounds

2.2.1 Preprocessing

At first the original signal is decimated by factor 4 from 8000 Hz to 2000 Hz and the a normalization process is applied as follows:

$$x_{norm}(t) = \frac{x(t)}{\left|\max(x(t))\right|} \quad (1)$$

2.2.2 Localization and segmentation of heart Sounds

The localization algorithms operating on PCG data try to emphasize heart sound occurrences with an initial transformation that can be classified into three main categories: frequency based transformation, morphological transformations and complexity based transformations [1].

Modified S-transform and Shannon Energy (MSSE) localization method: MSSE envelope(Fig. 3).

We have proposed a method named SSE in [13] to segment the heart sound. This method is based on the S-transform and the Shannon energy. The SSE method operates on the local spectrum calculated by the S-transform.

The proposed SSE method calculates the Shannon energy of each column of the extracted S-matrix as follows:

$$SSE(x_i) = -\int_{-\infty}^{+\infty} |S_x(\tau, f)|^n \log(|S_x(\tau, f)|^n) df \quad (2)$$

Where $S_x(\tau, f)$ is the S-transform of the signal $x(t)$ [22]:

$$S_x(\tau, f) = \int_{-\infty}^{+\infty} x(t) w(t-\tau, f) e^{-2\pi jft} dt \quad (3)$$

The parameter *n* in equation [23] is usually fixed to 2 which is the standard coefficient of the Shannon energy measure. The parameter n can be fixed to 1.5 for example to enhance the detection of low intensities sounds buried in noise. This occurs in heart sounds more often with S2 when the cardiac frequency is high. Fig. 4 shows the compromise of attenuation of low and high intensities, as a function of the value of n. we note here that for the SSE method, the intensities are the local spectrum coefficients of the S-transform and not the time sample intensities of the signal.

Figs. 5 and 6 shows the SSE envelope extract for normal noisy heart sounds and pathological heart sounds, respectively.
When the first and the second heart sounds are localized by the SSE method the OSSE [3,13] method is applied to segment these sounds.

The block diagram of the OSSE algorithm is shown below (Fig. 7).

First it consists to estimate the limit boundaries for each located sound by applying a window of 150 ms. Then the Stockwell transform of each segmented bound is optimized. The SSE envelope is recalculated based on the new (optimized) representation and finally a local threshold is applied to estimate the refined boundaries.

Figs. 8, 9 and 10 shows figures show the process to achieve the signal analysis and detection of S1 and S2.

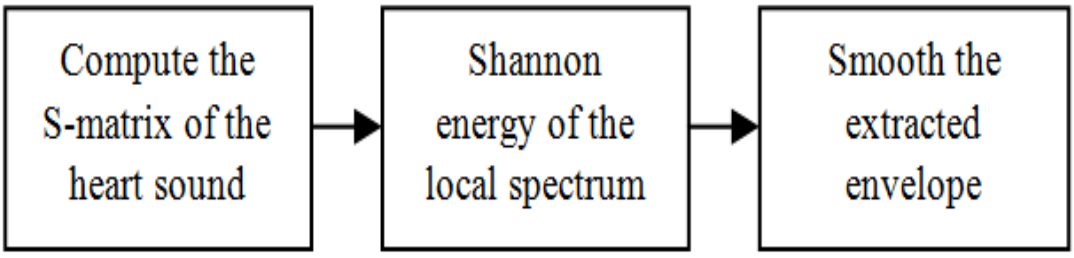

Fig. 3. Block diagram of SSE method

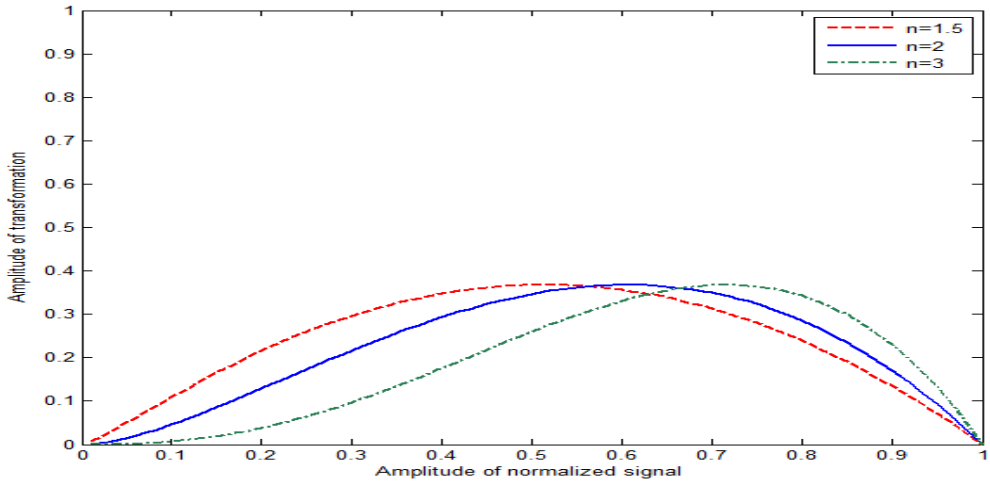

Fig. 4. The envelope of normalized signal for values of n=1.5, 2 and 3

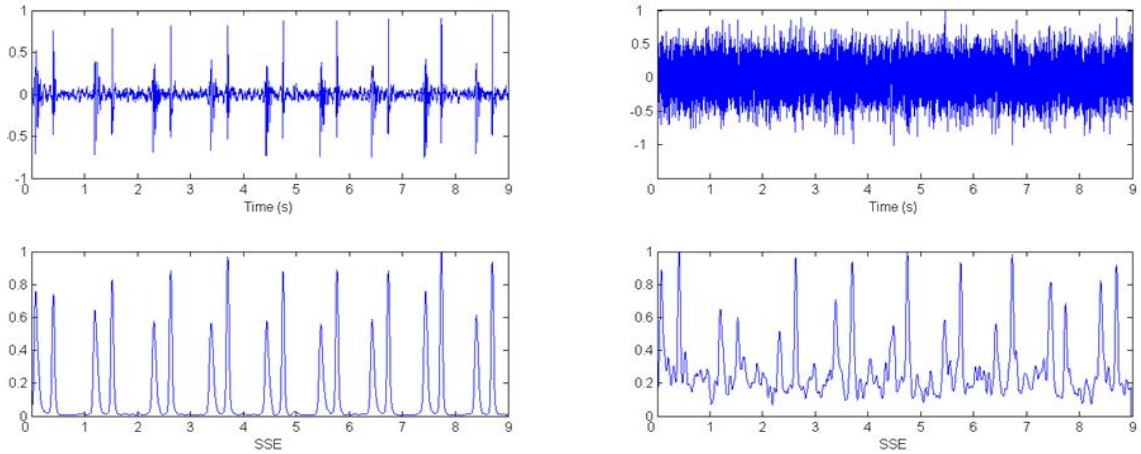

Fig. 5. (top) Envelope extraction for two normal PCG signal without and with additive Gaussian noise, (bottom) their SSE envelopes

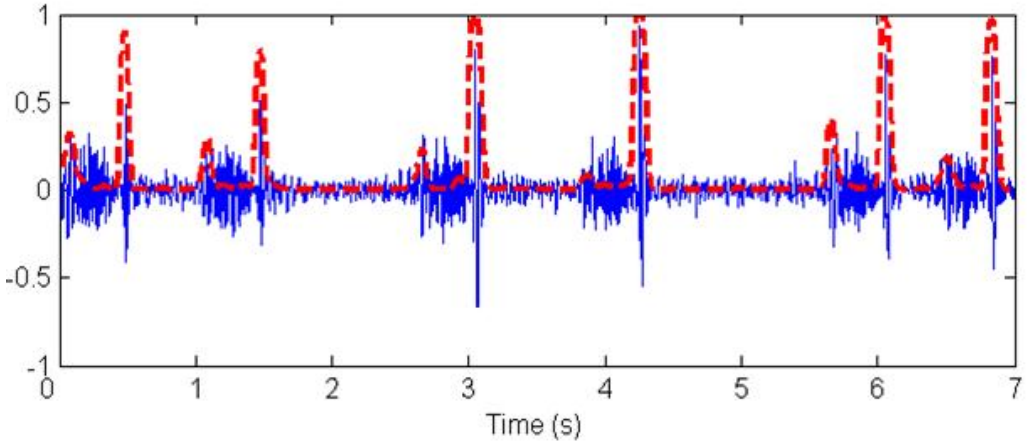

Fig. 6. The SSE Envelope (dashed lines) for a signal with systolic murmur

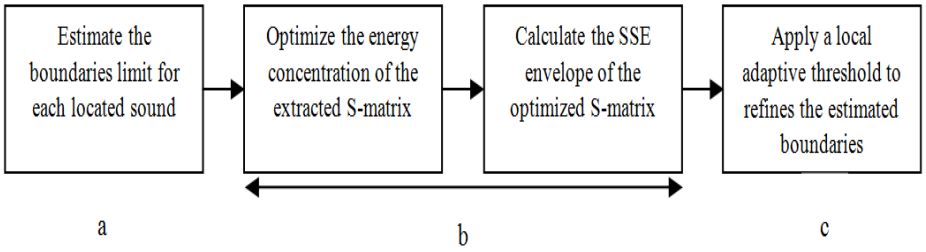

Fig. 7. The block diagram of the OSSE Method

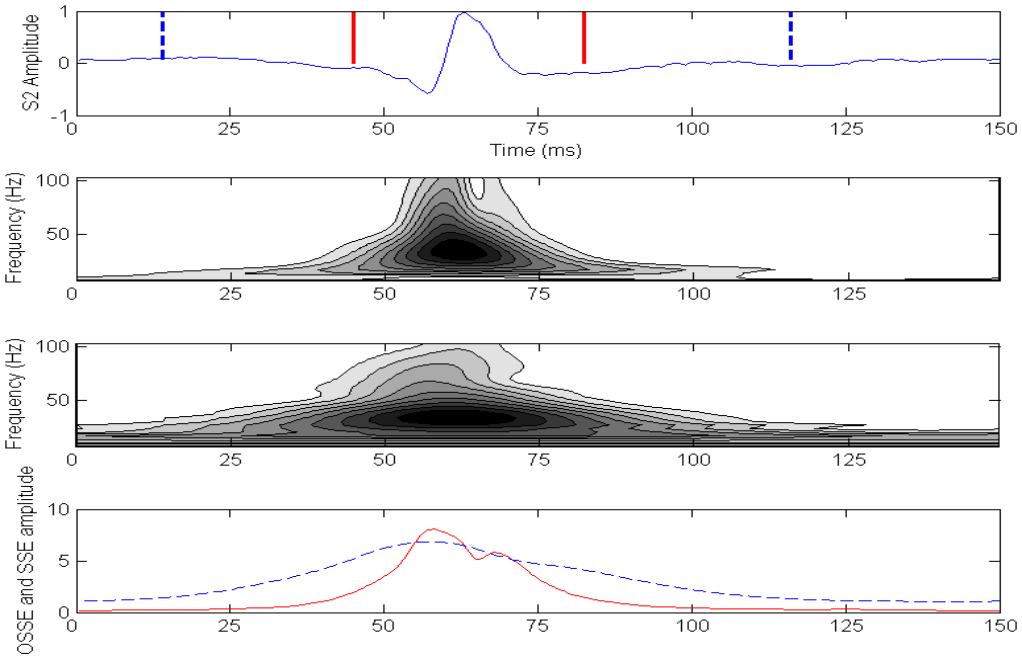

Fig. 8. (top) S2 signal with two detected boundaries calculated by the optimized S-transform and the standard S-transform (dashed line), S-transform with the optimum valueα=0.5, standard S-transform withα=1, (bottom) SSE envelope for the optimized S-transform and standard S-transform (dashed line)

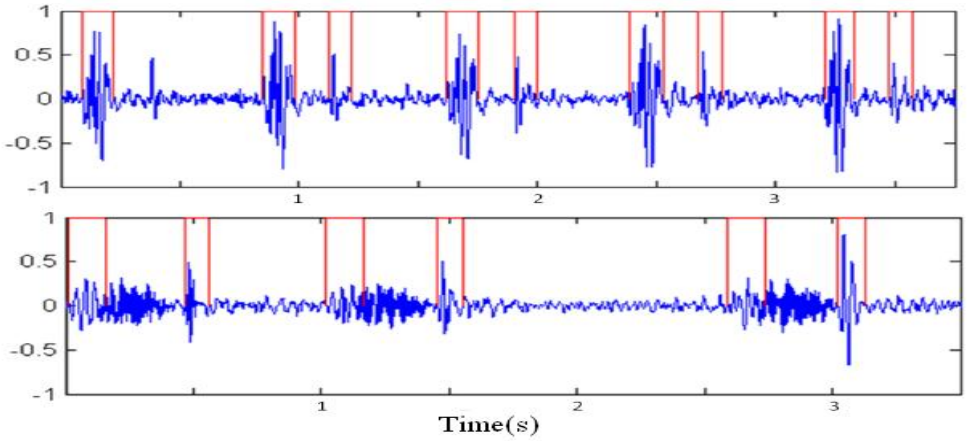

Fig. 9. OSSE method applied on a normal heart sound (top) and pathological heart sound (bottom)

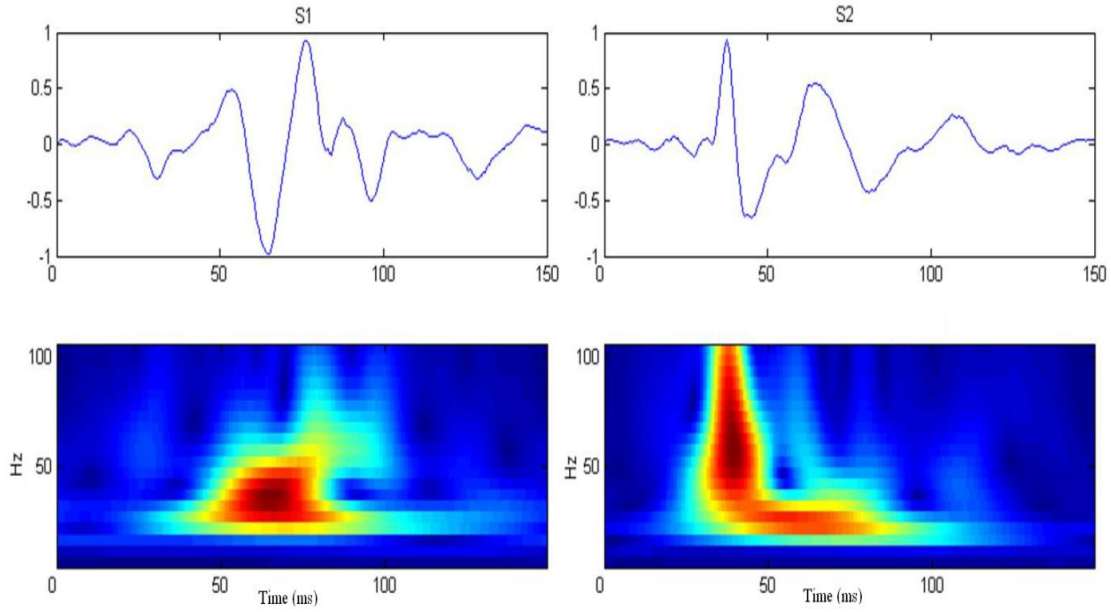

Fig. 10. S1 and S2 signals (top), optimized S-transform obtained with α=0.8 for S1 and α=0.5 for S2 (bottom)

2.3 Classification of Heart Sounds

2.3.1 S1 and S2 Classification

a. The Gaussian parameter α as discriminant feature

A new feature based on the energy concentration in time frequency domain is used to classify the first and the second heart sounds. This feature is used to optimize the energy concentration of the S-transform as follows:

$$\alpha_{opt} = \arg\max_{\alpha}(CM(\alpha)) \quad (4)$$

Where CM is the energy concentration measure that we aim to optimize [13].

b. The SSE envelope feature: β

A second feature investigated in this study, named β, it aims to integrate the normalized SSE envelope over time, and it can be given as:

$$\beta = \int_{-\infty}^{+\infty}\left\{\int_{-\infty}^{+\infty}|S_x(t,f)|^2\log(|S_x(t,f)|^2)df\right\}dt \quad (5)$$

The SSE envelope estimates the frequency energy at the local spectrum of the signal. It can be considered as a modified instantaneous frequency measure. The β feature aims to reveal the frequency contribution of each sound over time. Mathematically, it can be viewed as the integration over time of a modified instantaneous frequency measure. Physically, this feature reveals in some way the shape morphology of the signal. The measure is computed from the normalized SSE envelope to avoid the influence of the amplitude variations.

Fig. 11 shows an example of the β feature calculated on S1 and S2 sounds from their normalized SSE envelopes.

Murmurs detection: Normalized Shannon Entropy (NSE) [4]

Heart murmurs usually result from turbulence in blood flow or the vibration of heart tissues which can occur in a systolic or diastolic period. The presence of murmurs increases the heart sound complexity. Several recent studies use methods for nonlinear and chaotic signals to estimate the signal complexity and detect murmurs [20,23]. These methods are generally based on the reconstructed state space which explores the non-linear behavior and the non-Gaussian components of the signal. However, even though it seems reasonable to expect the nonlinear and chaotic characteristics of turbulence in blood flowthrough a vessel to be reflected in the murmurs, it is well accepted that recorded [5]

signals do not necessarily reflect the nonlinear and chaotic behavior of the underlying system [24,25]. Moreover, application of such methods suited for nonlinear or chaotic signals might be an unnecessary increase in algorithm complexity compared to linear methods based on autocorrelation and power spectrum [24,26]. Therefore, we apply the complexity measure on the TFR plane (ST-Spectrogram) instead of the reconstructed state space, to detect murmurs in heart sounds.

The Shannon Entropy is a natural candidate for measuring the complexity of a signal through TFR. It is applicable on the ST-Spectrogram coefficients (C_x) since the ST-spectrogram verifies the non-negativity condition. The Shannon Entropy is defined as follows:

$$H(C_x) = -\iint C_x(t,f)\log_2 C_x(t,f)dtdf \quad (6)$$

To normalize the Shannon entropy, we normalize first the coefficients of the ST-spectrogram as follows:

$$C_x^{norm}(t,f) = \frac{C_x(t,f)}{\iint C_x(u,v)dudv} \quad (7)$$

The maximum of Shannon Entropy, which correspond to equiprobable events case, can be given as:

$$H_{\max}(C_x^{norm}) = \log_2(n \times m) \quad (8)$$

Where, n is the samples number of the signal $x(t)$, m is the number of frequency voices used to calculate the ST-spectrogram and $n \times m$ is the total number of coefficients in the $C_x^{norm}(t,f)$ distribution. Therefore, the normalized Shannon Entropy can be given as:

$$H_{norm}(C_x^{norm}) = \frac{H(C_x^{norm})}{\log_2(n \times m)} \quad (9)$$

The peaky TFRs of signals comprised of small numbers of elementary components would yield small entropy values, while the diffuse TFRs of more complicated signals would yield large entropy values. Fig. 12 shows an example of normal and pathologic systolic sounds and their NSEs based on ST-Spectrogram [27,28]. The number of component in pathologic sound with the presence of murmur is higher than the normal systole, which explains the higher NSE (0.88) [29].

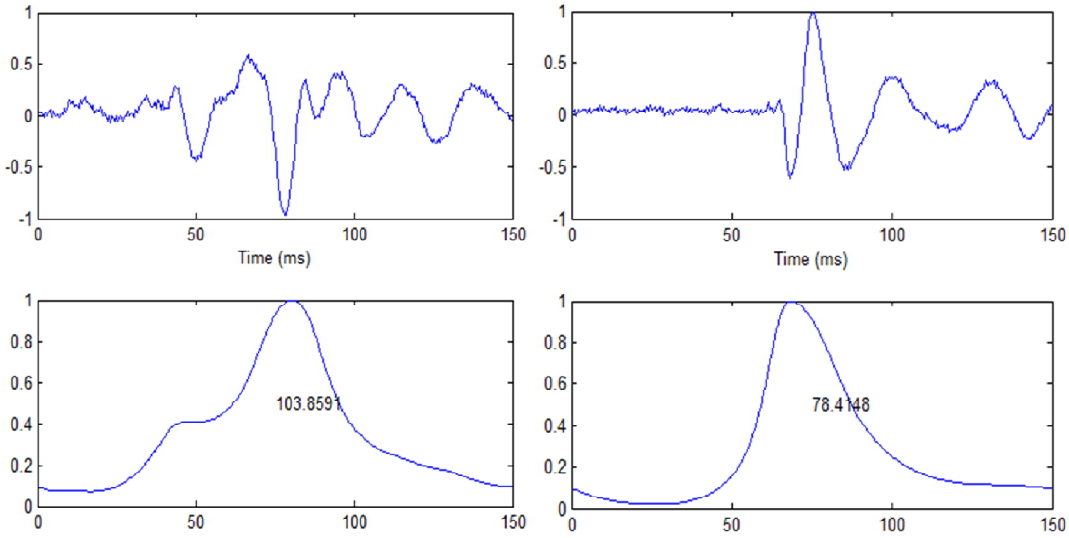

Fig. 11. S1 (left) and S2 signals (right) and their normalized SSE envelopes with the values of β (bottom)

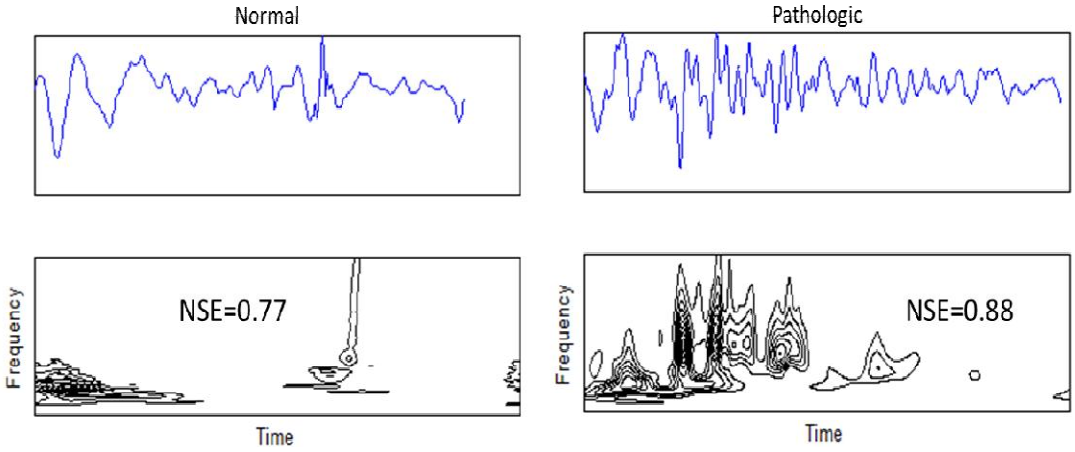

Fig. 12. NSEs applied on the ST-Spectrogram plane for normal and pathologic segmented

4. CONCLUSION

This paper presented several algorithms and methods to segment and classify the heart sounds (PCG signal) based on time-frequency domain. Heart sounds are accurate for diagnosing some heart diseases. They are non-stationary signals by nature (as most biosignals) which make the application of Time-Frequency based methods intuitive.

The paper focused on the application of the S-transform on heart sounds. Several theoretical methods are proposed and applied on real signals. Localization, segmentation, feature extraction and classification schemes of heart sounds are explored and discussed. A campaign of measurements is in motion in the Hospital University of Strasbourg to collect normal and pathological heart sounds which will allow us to test the proposed signal processing tools on large clinical datasets. The classification of murmurs from different origin and the assessing of their severity, the detection of additional sounds as S3 and S4 can be considered as future research perspectives to this work.

ETHICAL APPROVAL

All authors hereby declare that all experiments have been examined and approved by the ethics committee of the *University Hospital of Strasbourg* (Strasbourg, France, *PRI* Project) and have therefore been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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