STOCKWELL TRANSFORM OPTIMIZATION APPLIED ON THE DETECTION OF SPLIT IN HEART SOUNDS.

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ABSTRACT

The aim of this paper is to improve the energy concentration of the Stockwell transform (S-transform) in the time-frequency domain. Several methods proposed in the literature tried to introduce novel parameters to control the width of the Gaussian window in the S-transform. In this study, a modified S-transform is proposed with four parameters to control the Gaussian window width. A genetic algorithm is applied to select the optimal parameters which maximize the energy concentration measure. An application presented in this paper consists to detect split in heart sounds and calculate its duration which is valuable medical information. Comparison with other famous time-frequency transforms such as Short-time Fourier transforms (STFT) and smoothed-pseudo Wigner-Ville distribution (SPWVD) is performed and discussed.

Index Terms— Stockwell transform, energy concentration, genetic algorithm, heart sounds, valvular split.

1. INTRODUCTION

The Stockwell Transform (S-transform) can be considered as a hybrid between the Short Time Frequency Transform (STFT) and the wavelet transform [1]. It can be viewed as a frequency dependent STFT or a phase corrected wavelet transform. It has gained popularity in the signal processing community because of its easy interpretation and fast computation [2]. The S-transform has been shown high performance in classification and feature extraction problems applied on non-stationary signals, such as heart sounds [3–5], power quality signals [6], EEG signals [7] etc.

Classically the S-transform uses a Gaussian window, whose standard deviation varies over frequency. Whatever the analyzed signal, the width of the Gaussian window will decrease as the frequency increases. This produces a higher frequency resolution at lower frequencies and a higher time resolution at lower frequencies. However, the S-transform can suffer from poor energy concentration in time-frequency domain [8]; the window width of the classic S-transform can be considered as limitation since it doesnt take into consideration the nature of analyzed signal. It would be more appropriate to adapt the window to the signal in order to maximize the energy localization of the S-transform. The energy concentration in the Time-Frequency (TF) domain is a very important factor for the algorithms that aim to detect or extract relevant feature from time-frequency domain. Hence, the importance of an energy concentration optimization process to improve the segmentation and the classification of non-stationary signals. As it is well known, the ideal time-frequency transformation should only be distributed along frequencies for the duration of signal components. So the neighboring frequencies would not contain any energy and the energy contribution of each component would not exceed its duration [9].

Many studies tried to improve the Time-Frequency (TF) representation of the S-transform by controlling better the parameters of the Gaussian window [10–14]. The main study in the literature interested to optimize the energy concentration directly in the TF domain was the study of Sejdic et al. [15]. That is, to minimize the spread of the energy beyond the actual signal components. The authors tried to introduce a new parameter to the Gaussian window modulation and vary it to maximize the concentration energy measure.

The main contribution of this paper is the optimization of the S-transform energy concentration. For that, new parameters are introduced to control better the width of the Gaussian window and a Genetic Algorithm is applied to select properly these parameters. A direct application of the proposed method is the detection of split in heart sounds which can be considered as valuable medical information [16]. We show the importance of the time-frequency resolution enhancement in order to detect accurately split and to calculate its duration. The new modified S-transform is compared with the method proposed by Sejdic et al. [15] and other time-frequency representations such as STFT and SPWVD.

This paper is organized as follows: Section 2 presents the proposed modified S-transform with the optimization process based on genetic algorithm. Section 3 presents the application on heart sounds proposed in this paper. Section 4 compares the proposed method with other TFRs and shows the results of the split durations calculated on simulated heart sounds. Finally, section 5 gives the conclusion and the future work.

The authors would like to thank the financial support from the French telemedicine project, E-Care

2. STOCKWELL TRANSFORM OPTIMIZATION

2.1. The original S-transform

The original S-Transform of a time varying signal is defined by [1]:

$$S_x(t,f)=\int_{-\infty}^{+\infty}x(\tau)w(\tau-t,f)e^{-2\pi jf\tau}d\tau \tag{1}$$

Where the window function $w(\tau-t,f)$ is chosen as:

$$w(t,f)=\frac{1}{\sigma(f)\sqrt{2\pi}}e^{\frac{-t^2}{2\sigma(f)^2}} \tag{2}$$

And $\sigma(f)$ is a function of frequency as:

$$\sigma(f)=\frac{1}{|f|} \tag{3}$$

The window is normalized as:

$$\int_{-\infty}^{+\infty}w(t,f)dt=1 \tag{4}$$

This gives the direct relation between the S-transform and the Fourier spectrum by averaging the local spectrum over time:

$$\int_{-\infty}^{+\infty}S_x(t,f)dt=X(f) \tag{5}$$

Where $X(f)$ is the Fourier transform of $x(t)$. The signal $x(t)$ can be recovered from $S_x(t,f)$ as follows:

$$x(t)=\int\limits_{-\infty}^{+\infty}\left\{\int\limits_{-\infty}^{+\infty}S_x(\tau,f)\right\}e^{i2\pi ft}df\,d\tau \tag{6}$$

2.2. The modified S-transforms in the literature

To control better the resolution of the S-transform, McFadden et al. [11] and later Pinnegar and Mansinha [10, 12] introduced the generalized S-transform with a set of parameters that determine the shape and properties of the window. For the Gaussian window, the parameter is introduced as follows:

$$w(\tau-t,f)=\frac{|f|}{\gamma\sqrt{2\pi}}e^{\frac{-f^2(\tau-t)^2}{2\gamma^2}} \tag{7}$$

This allows a better control of the time-frequency resolution of the S-transform by controlling the width of the Gaussian window. Another way to control the width of the window in the S-transform is proposed by Sejdic et al. [15] and consists to fix γ to 1 and introduce a new parameter r as follows:

$$w(\tau-t,f)=\frac{|f|^r}{\sqrt{2\pi}}e^{\frac{-f^{2r}(\tau-t)^2}{2}} \tag{8}$$

The authors vary the parameter r until the maximum of the energy concentration measure is reached.

2.3. The proposed S-transform

In this paper, we propose to introduce a new Gaussian window with the follows standard deviation:

$$\sigma(f)=\frac{mf^p+k}{f^r} \tag{9}$$

In this case $\gamma=mf^p+k$ and the modified Gaussian window can be given as:

$$w(\tau-t,f)=\frac{|f|^r}{(mf^p+k)\sqrt{2\pi}}e^{\frac{-(\tau-t)^2f^{2r}}{2(mf^p+k)^2}} \tag{10}$$

The parameter $f^r/(mf^p+k)$ represents the number of cycles (periods) of a frequency that can be contained within one standard deviation σ of the Gaussian window. The introduced parameters m,p,k and r aim to give more flexibility to the Gaussian window. The modified S-transform becomes:

$$S_x^{m,p,k,r}(\tau,f)=\int\limits_{-\infty}^{+\infty}x(t)\frac{|f|^r}{(mf^p+k)\sqrt{2\pi}}e^{\frac{-(\tau-t)^2f^{2r}}{2(mf^p+k)^2}}e^{-i2\pi ft}dt \tag{11}$$

The new window satisfies the normalization condition for the original S-transform window which insures the invertibility of the modified S-transform:

$$\int\limits_{-\infty}^{+\infty}\frac{|f|^r}{(mf^p+k)\sqrt{2\pi}}e^{\frac{-(\tau-t)^2f^{2r}}{2(mf^p+k)^2}}dt=1 \tag{12}$$

2.3.1. Generate optimal parameters by using a genetic algorithm

A crucial question is how to choose the parameters of the Gaussian window? Select empirically the values ofm,p,k and r will may not be adequate for some types of signals. It will be more appropriate to generate automatically adaptive parameters which respect the nature of analyzed signal. In this paper, we propose to apply a genetic algorithm to select automatically the parameters m,p,k and r (see Fig. 1). Genetic Algorithm (GA) based on the mechanisms of natural selection and genetics, has been developed since 1975 [17]. GA has been proven to be very efficient and stable in searching for global optimum solutions. Usually, a simple GA is mainly composed of three operations: selection, genetic operation, and replacement [18].

The fitness function used in this paper is the energy concentration measure proposed in [19]. By applying this measure to the modified S-transform, we obtain:

$$CM(m,p,k,r)=\frac{1}{\int\limits_{-\infty}^{+\infty}\int\limits_{-\infty}^{+\infty}\left|S_x^{m,p,k,r}(t,f)\right|dtdf} \tag{13}$$

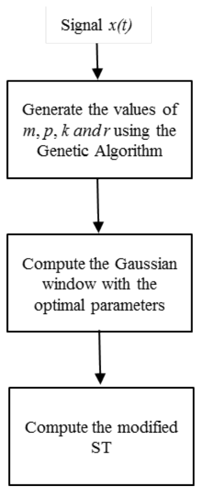

Fig. 1. The proposed optimization module.

Where the modules of the S-transform is normalized as:

$$\overline{S_x^{m,p,k,r}(t,f)} = \frac{S_x^{m,p,k,r}(t,f)}{\sqrt{\int\limits_{-\infty}^{+\infty}\int\limits_{-\infty}^{+\infty}\left|S_x^{m,p,k,r}(t,f)\right|^2 dtdf}} \tag{14}$$

Then, the optimization problem can be expressed as follows:

$$\underset{m,p,k,r}{\arg\max}\left(\int\limits_{-\infty}^{+\infty}\int\limits_{-\infty}^{+\infty}\left(1/\left|\overline{S_x^{m,p,k,r}(t,f)}\right|\right)dtdf\right) \tag{15}$$

where m, p, k and $r \in]0,3]$. The GA parameters are choosen empirically; The population size is 20, the cross over rate is 0.8, the mutation rate is 0.05 and the chromosome length is 4(since we have 4 variables to optimize: m, p, k and r).

3. APPLICATION ON THE DETECTION OF SPLIT IN HEART SOUNDS

The analysis of the cardiac sounds solely based on the human ear is limited by the experience of the clinician for a reliable diagnosis of cardiac pathologies and to obtain all the qualitative and quantitative information about cardiac activity. Proposing an objective signal processing methods able to extract relevant information from heart sounds is a great challenge for specialists and auto-diagnosis fields. The electronic stethoscope is capable to register and optimize the quality of the acoustic heart signal, completed by the PhonoCardio-Graphic (PCG) presentation of the auscultation signal. The localization of the first and the second heart sounds (S1 and S2), the number of their internal components, their frequential content, etc. can be considered as pertinent information very useful for patricians and for classification systems [5]. The application proposed in this paper consists to detect splits in heart sounds. The split within the S1 and the S2 heart sounds

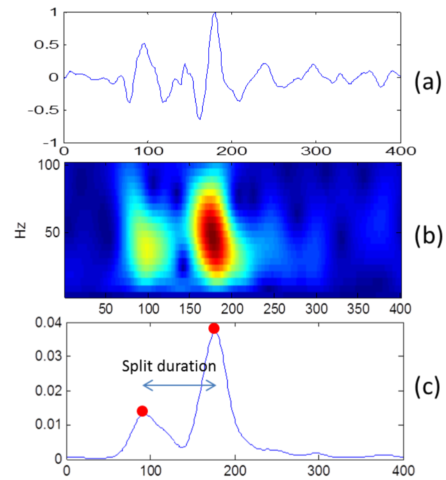

Fig. 2. Example of split detection in the first heart sound; (a) S1 extracted from real heart sound; (b) The proposed optimized S-transform of the heart sound; (c) The extracted envelope with the detected local extrema corresponding to the two components of the heart sound.

emerged as an indicator of several valvular diseases [16]. In addition, the PCG signal is a powerful tool for assessing the pulmonary artery pressure. Xu et al. found out that the pulmonary artery pressure is correlated with the split in S2 [20]. We use the modified S-transform proposed in this paper to detect split and calculate its duration. The optimization of the time-frequency representation of heart sounds can lead to more objective and reliable methods and diagnostics. The proposed algorithm to detect splits in heart sounds can be summarized as follows:

- First, the heart sound is segmented by using the proposed algorithm in [5] to detect the first and the second heart sounds.
- We calculate the optimized S-transform $S_x^{m,p,k,r}$ for each segmented sound.
- Then, we calculate the envelope of the segmented sound x_i based on the optimized S-transform as follows:

$$Env(x_i) = -\int\limits_{-\infty}^{+\infty}\left|S_x^{m,p,k,r}(\tau,f)\right|^2 \log(\left|S_x^{m,p,k,r}(\tau,f)\right|^2)df \tag{16}$$

- Finally, we apply an algorithm to detect the local extrema of the extracted envelope.

Normally, a heart sound with split is supposed to have two local extrema in its extracted envelope. The duration of split is calculated as the distance between the two detected ex-trema. Figure 2 shows the optimized S-transform calculated for a real heart sound S1 with split and its extracted envelope.

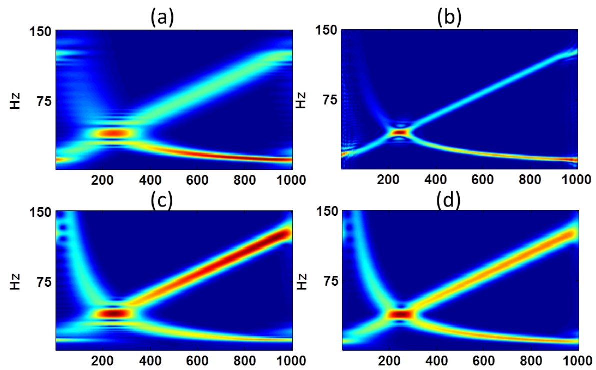

Fig. 3. Time-Frequency representation of the test signal: (a) STFT; (b) SPWVD; (c) S-transform proposed by Sejdic et al.; (d) the proposed S-transform

4. RESULTS AND DISCUSSIONS

Firstly, we apply the proposed S-transform on test signal and real heart sound and we compare the energy concentration with other time-frequency representations: the modi-fied S-transform proposed by Sejdic et al. [15], the Short-time Fourier Transform (STFT) and the smoothed-pseudo Wigner-Ville distribution (SPWVD). Then, we apply the proposed method on a simulated S2 sound with various split durations.

4.1. Energy Concentration

A test signal of two crossing components and a real heart sound (HS) S1 are used as example to compare between the different time-frequency representations (see Fig. 3 and 4). Table 1 shows the different concentration measures (CM) for each signal.

CM	STFT	SPWVD	ST-Sej	Proposed
Test signal	0.0042	0.0055	0.0045	0.005
Real HS	0.0126	0.016	0.0136	0.0147

Table 1. Shows the concentration energy measures (CM) applied on a synthetic signal and a real heart sound S1 (HS).

Figure 3 shows the time-frequency representation of the different transforms applied on the test signal. The SPWVD gives a very good energy concentration, however in the multicomponent zone the transform still suffer from interference terms and from poor resolution for the non-linear chirp component at high frequencies. The optimization of the ST proposed in [15] gives a good energy concentration for middle and high frequencies but its performance de-creases in low frequencies. The proposed S-transform in this paper gives a good compromise overall the time frequency plane (see Figure 3 (d) and Table 1 CM=0.005).

4.2. Split detection in heart sounds based on the optimized S-transform

We generate simulated S2 heart sounds with various split durations. The detection algorithm (section 3) is applied and the durations of splits are calculated. The S2 simulated signals used are based on the model proposed in [20].

Split(ms)	30	45	60
Error(S2)	2	3.2	4.3
Error(S2+Noise)	-	4.1	5.6

Table 2. Shows the duration split error (ms) calculated by the proposed algorithm for simulated S2 sound with various split durations without and with additive Gaussian noise

Measures in Table 2 are performed on one simulated S2 sound without and with additive noise. The optimized S-transform shows clearly its ability to detect and calculate split duration in heart sounds (error lower than 6 ms in presence of noise).

5. CONCLUSION

We presented in this paper a new method to improve the energy concentration of the Stockwell transform. The proposed method is based on a modified Gaussian window with a standard deviation controlled by four parameters. The new window is more flexible hence more adaptive to the analyzed signal. The parameters of the window are chosen by a Genetic Algorithm that selects the parameters which maximize the energy concentration in the time-frequency domain. Comparison with other famous time-frequency transforms such as STFT, SPWVD and other modified ST proposed in the literature is performed. First, the different methods are applied on a test signal and a real heart sound and the corresponding energy concentration measures are compared. Then, the performance of the proposed S-transform is confirmed on simulated heart sounds (S2) with various split durations. The method can be useful to other applications related to non-stationary signals. Finally, more measures on real heart sounds and theoretical signals are still needed.

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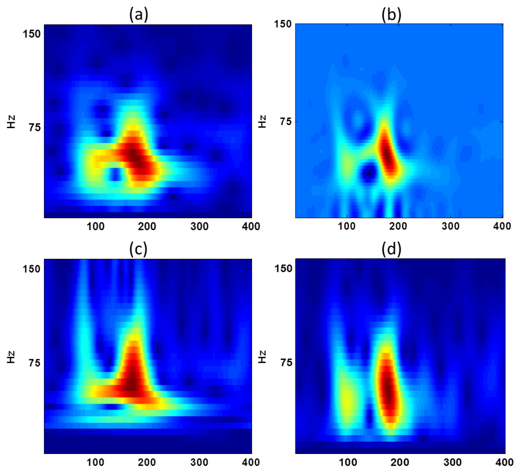

Fig. 4. Example of split detection in the first heart sound; (a) S1 extracted from real heart sound; (b) The proposed optimized S-transform of the heart sound; (c) The extracted envelope with the detected local extrema corresponding to the two components of the heart sound.

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