Time-Frequency analysis applied on segmentation and classification of heart sounds.

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Introduction

1. Electronic stethoscope
2. Heart sounds
3. E-care Project

PCG signal processing methods

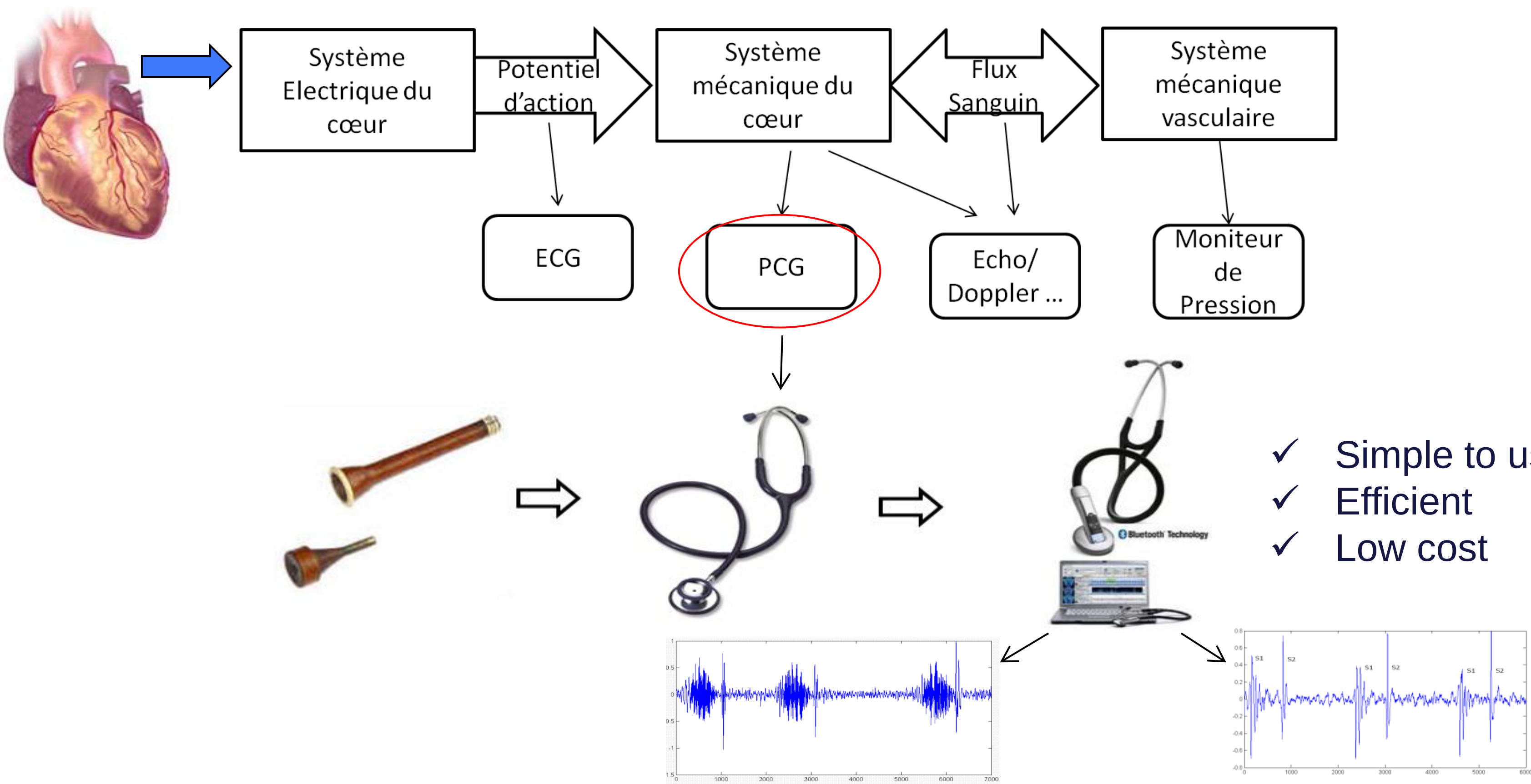
1. The Stockwell Transform
2. Localization: The SSE method
3. Segmentation: The OSSE method
4. S1 & S2 Classification
5. Murmur detection

DataBase and Results

1. DataBase
2. Results

Conclusion and Future work

Electronic stethoscope



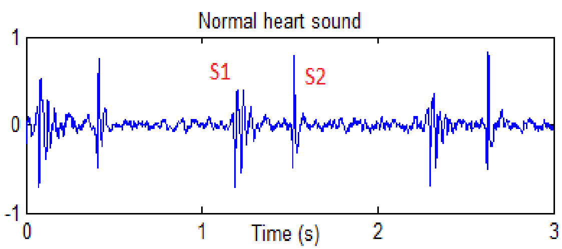
- ✓ Simple to use
- ✓ Efficient
- ✓ Low cost

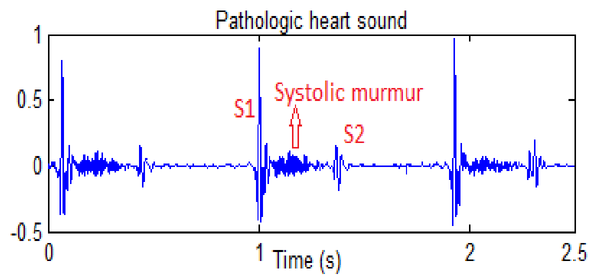
- Tool with embedded autonomous analysis, simple for home use by the general public for the purpose of auto-diagnosis, monitoring and warning in case of necessity.

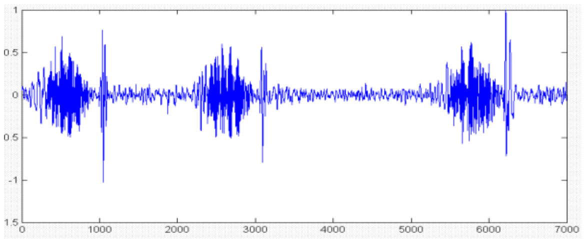
- Tool with sophisticated analysis (coupled to a PC, Bluetooth link) for the use of professionals in order to make an in-depth medical diagnosis and to train the medical students.

Heart Sounds

PCG signals : complexity and information-rich







- Time aspect
    - Localization
    - Segmentation
- Frequency aspect
    - S1 & S2 and their components signatures
    - Murmurs and additional sounds signature

E-care project

- Provide an intelligent platform useful for home monitoring by using a non-intrusive sensors for patients with heart failure stage 3 (NYHA classification).

- A infrastructure installed at a patient's home or medical service institute to collect vital data and signals : weight, body temperature, oximeter, PCG, ECG and lung sounds.

- Help the medical stuff by automating the processing of information given by these sensors to detect and anticipate the critical situation (intelligent design ontologies and reasoning associated with all collected features).

- Main implication of MIPS: Develop original signal processing methods and algorithms to analyze and classify biomedical signals

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Database and Results

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2. Results

Conclusion & Future work

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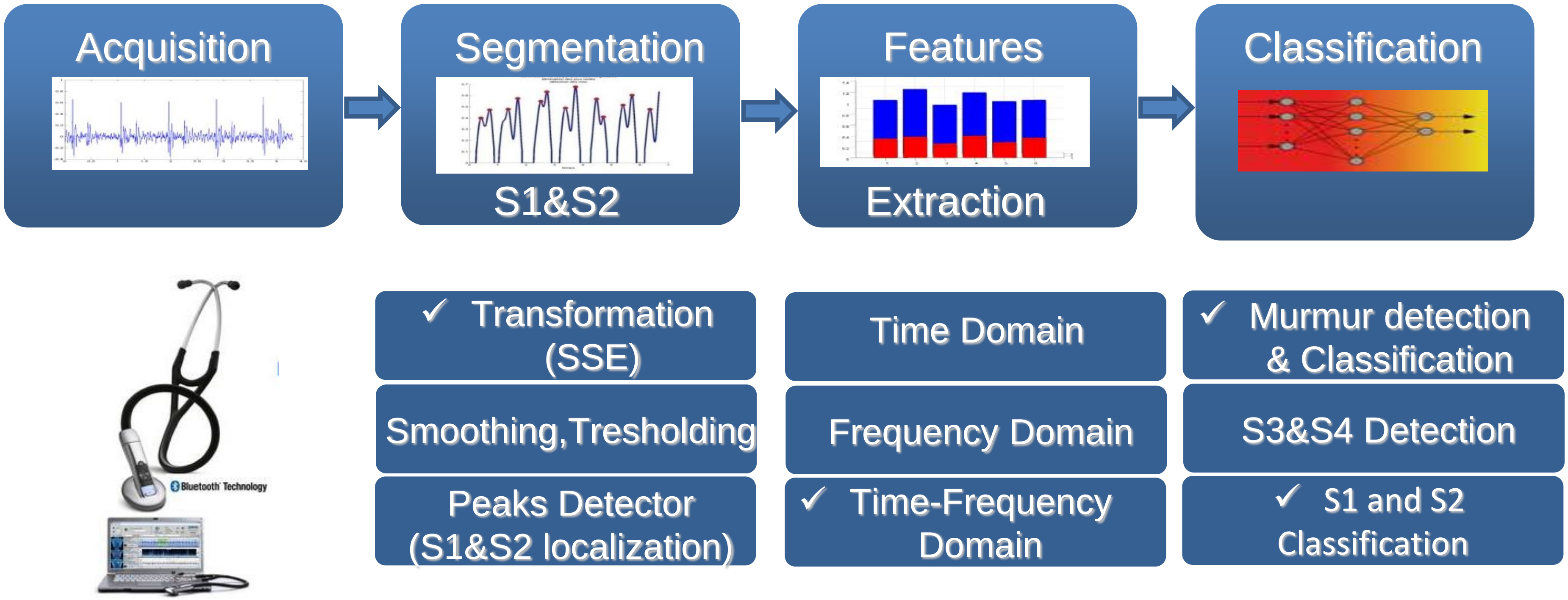
2. Results

Analysis module



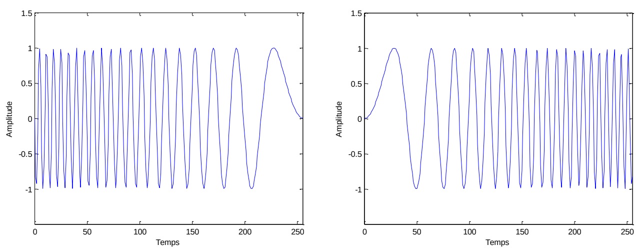
Time-Frequency Representations (TFRs)

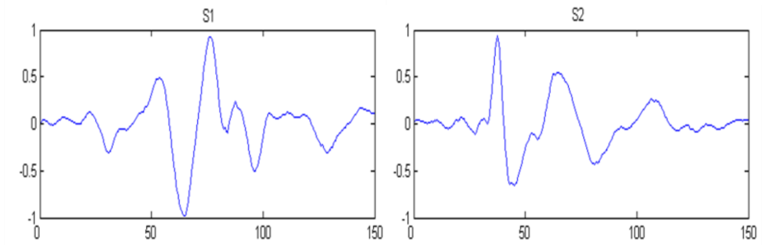
Non-stationary signals

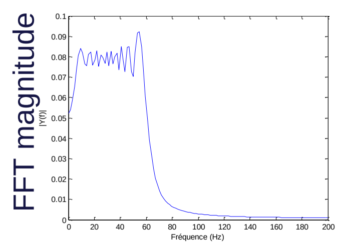
Two different Chirp Signals

Frequency varies over time

First and second heart sounds

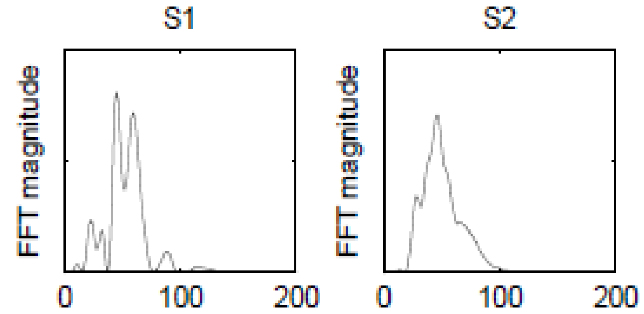


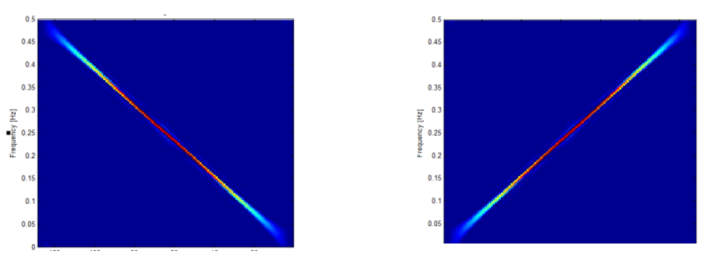




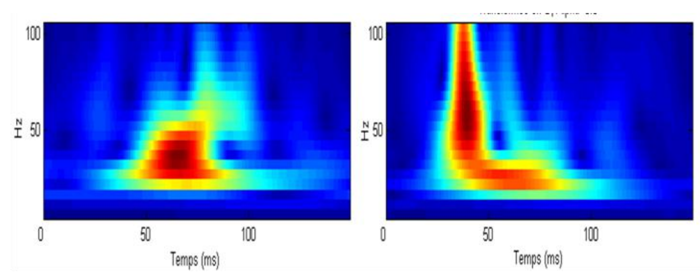
FFT limitations

Time information in frequency domain?





TFRs



The S-Transform [Stockwel96]

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) g(t-\tau) e^{-i2\pi f t} dt$$

$$g(t,\sigma) = \frac{1}{\sigma(f)\sqrt{2\pi}} e^{\frac{-t^2}{2\sigma(f)^2}} \qquad \sigma(f) = \frac{1}{|f|}$$

- Direct relation with the Fourier Transform:

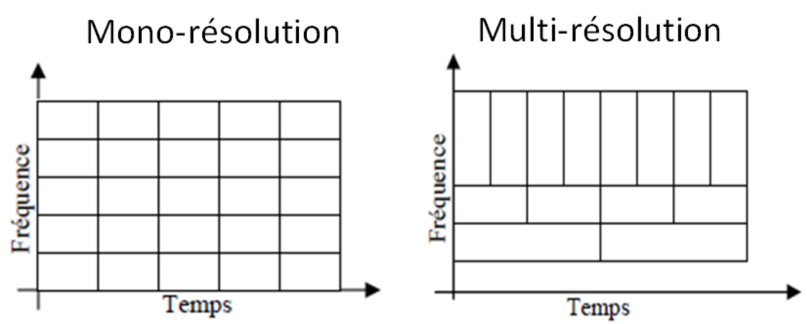
$$\int_{-\infty}^{+\infty} S(\tau, f) d\tau = X(f)$$

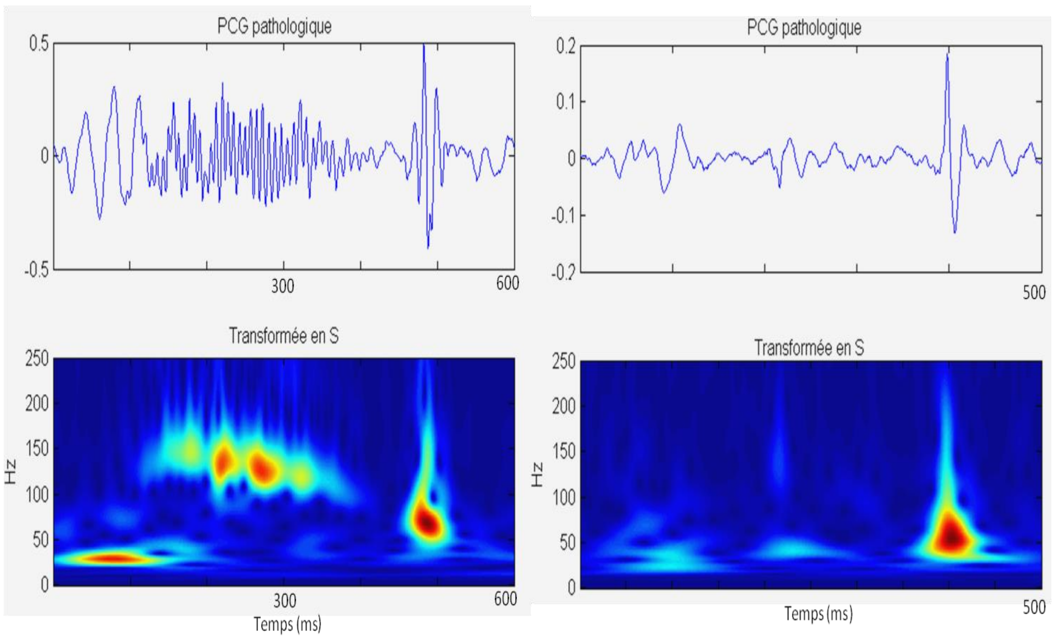
$$S(\tau, f) = \int_{-\infty}^{+\infty} X(\alpha + f) e^{\frac{-2\pi^2\alpha^2}{f^2}} e^{i2\pi\alpha\tau} d\alpha$$

- Relation with the Wavelet Transform:

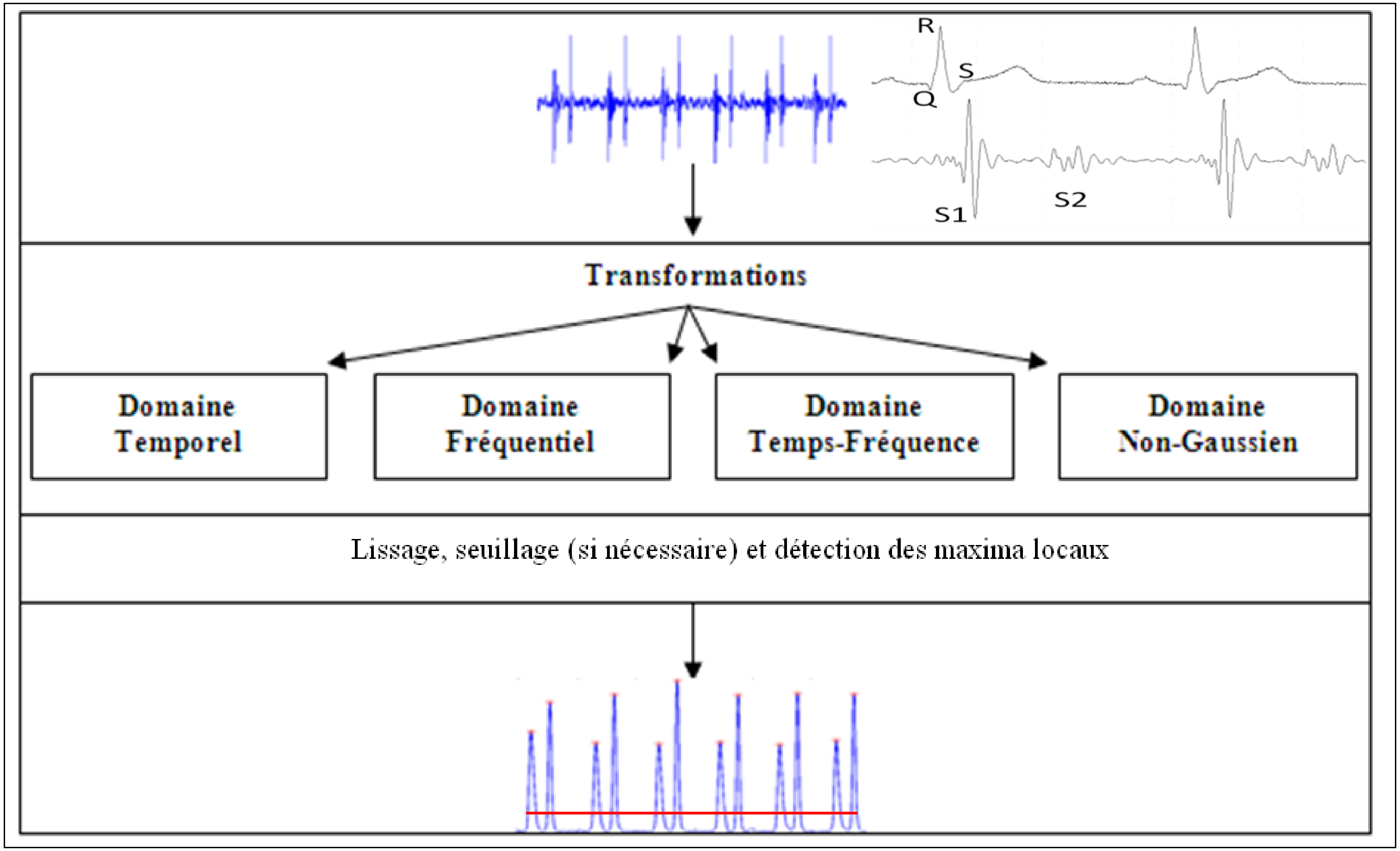
$$W(\tau, d) = \int_{-\infty}^{+\infty} x(t) w(t-\tau, d) dt$$

$$S(\tau, f) = e^{i2\pi f\tau} W(\tau, d) \qquad w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{-t^2 f^2}{2}} e^{-2\pi i f t}$$

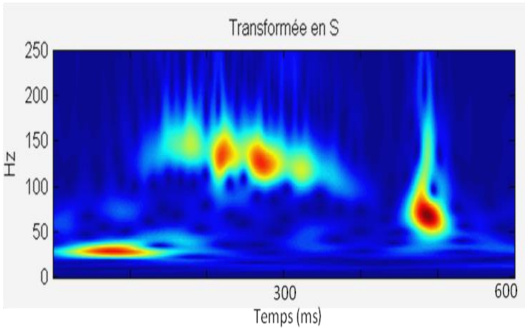




S1 & S2 localization: envelope extraction approach

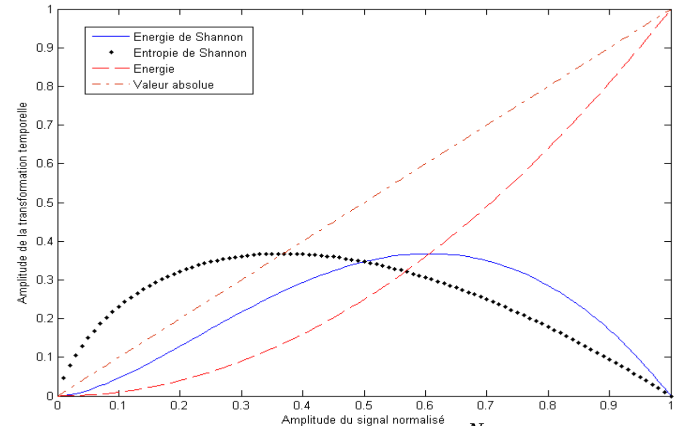


SSE method

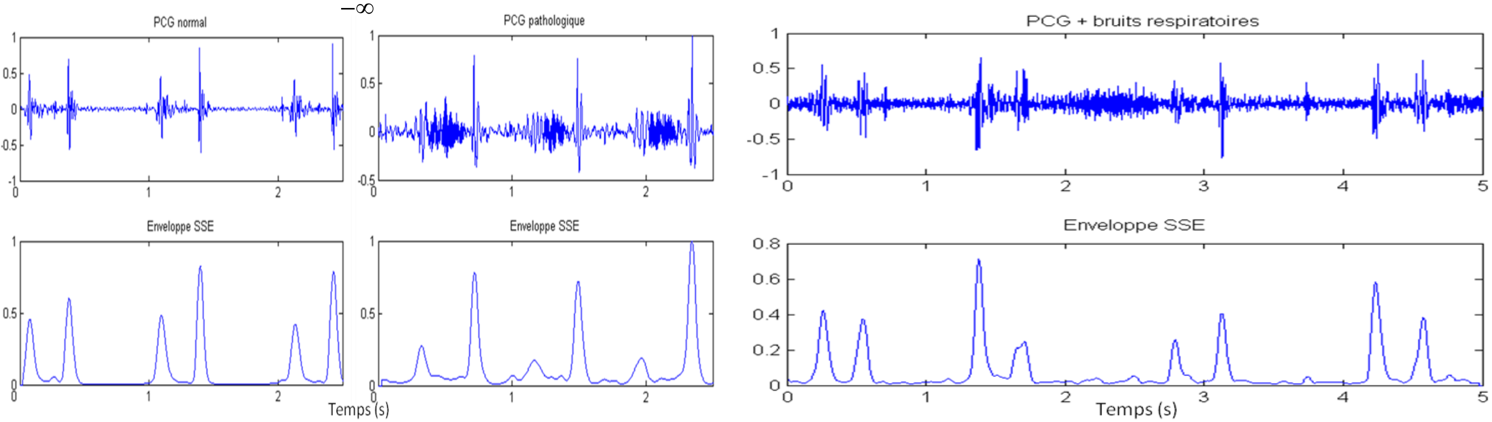


Compute the S-matrix of the heart sound → Shannon energy of the local spectrum → Smooth the extracted envelope

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

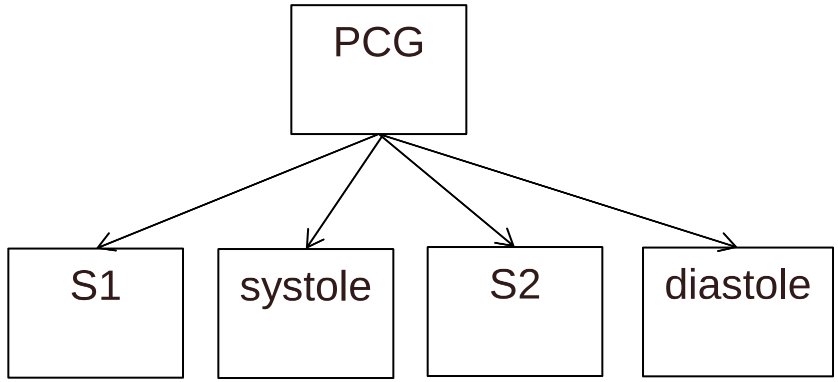


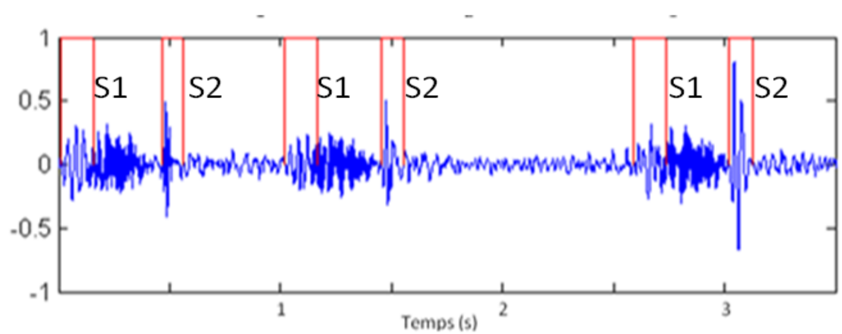
Shannon Energy $E_i = -\sum_{i=1}^{N} x^2(i).\log(x^2(i))$



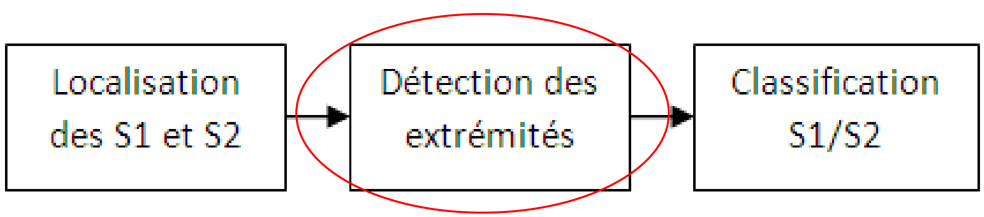
A. Moukadem, A. Dieterlen, C. Brandt, Automatic Heart Sound Analysis Module Based on Stockwell Transform. Applied on Auto-Diagnosis and Telemedicine Applications. eTELEMED 2013, 24-29 February, Nice, France.

Objectif





Segmentation of heart sounds



Classical approaches

Liang97, global threshold

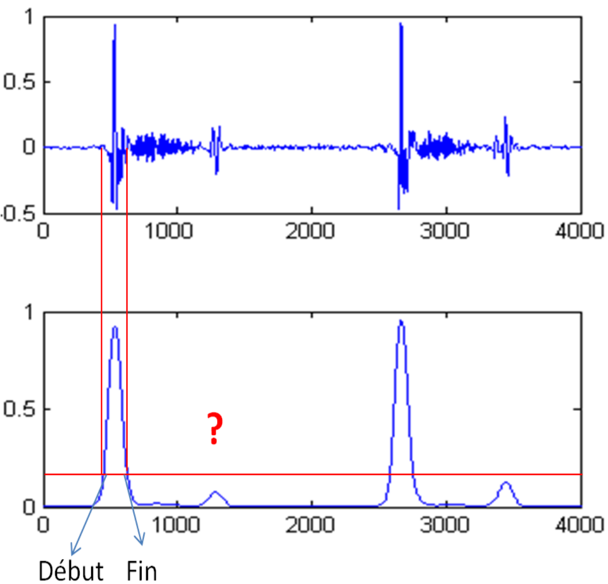
- Very sensitive to the selected threshold
- Ignore the local variations of the envelope

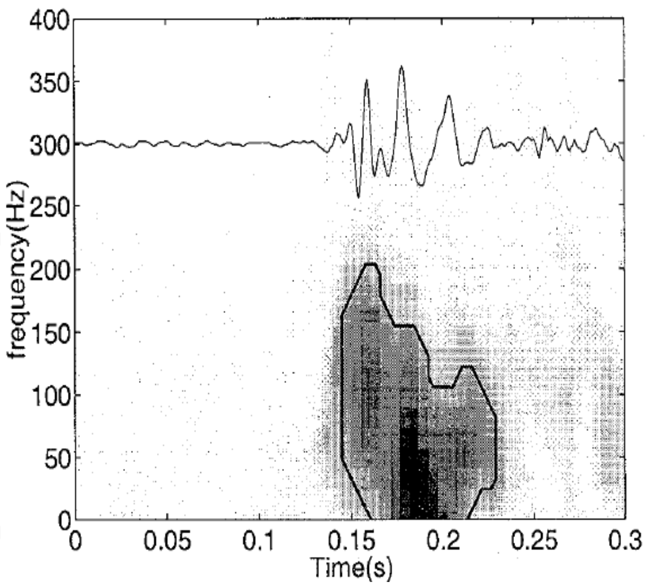
Liang98, local threshold

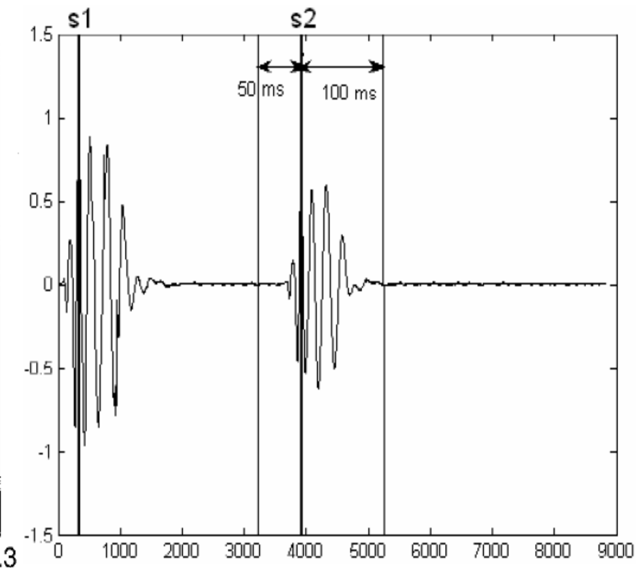
- STFT, 60% of TF energy
- Not validated

Ari06, biomedical features

- Very sensitive to noise





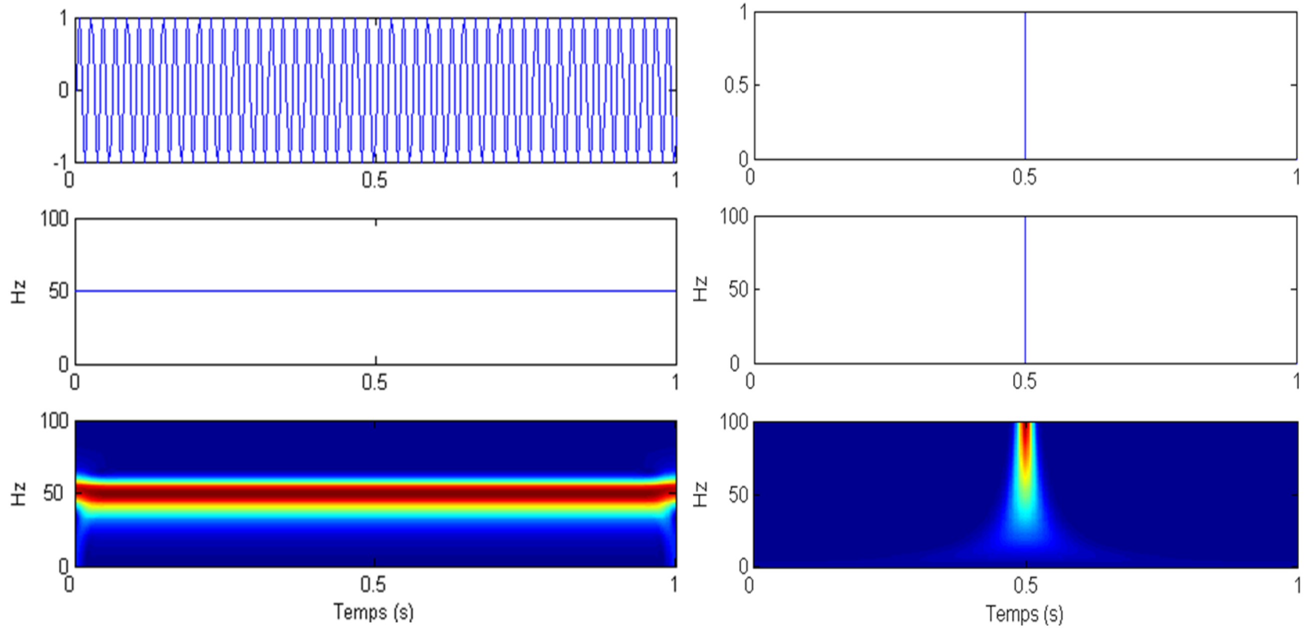


Ideal energy concentration in TF plane

Signals

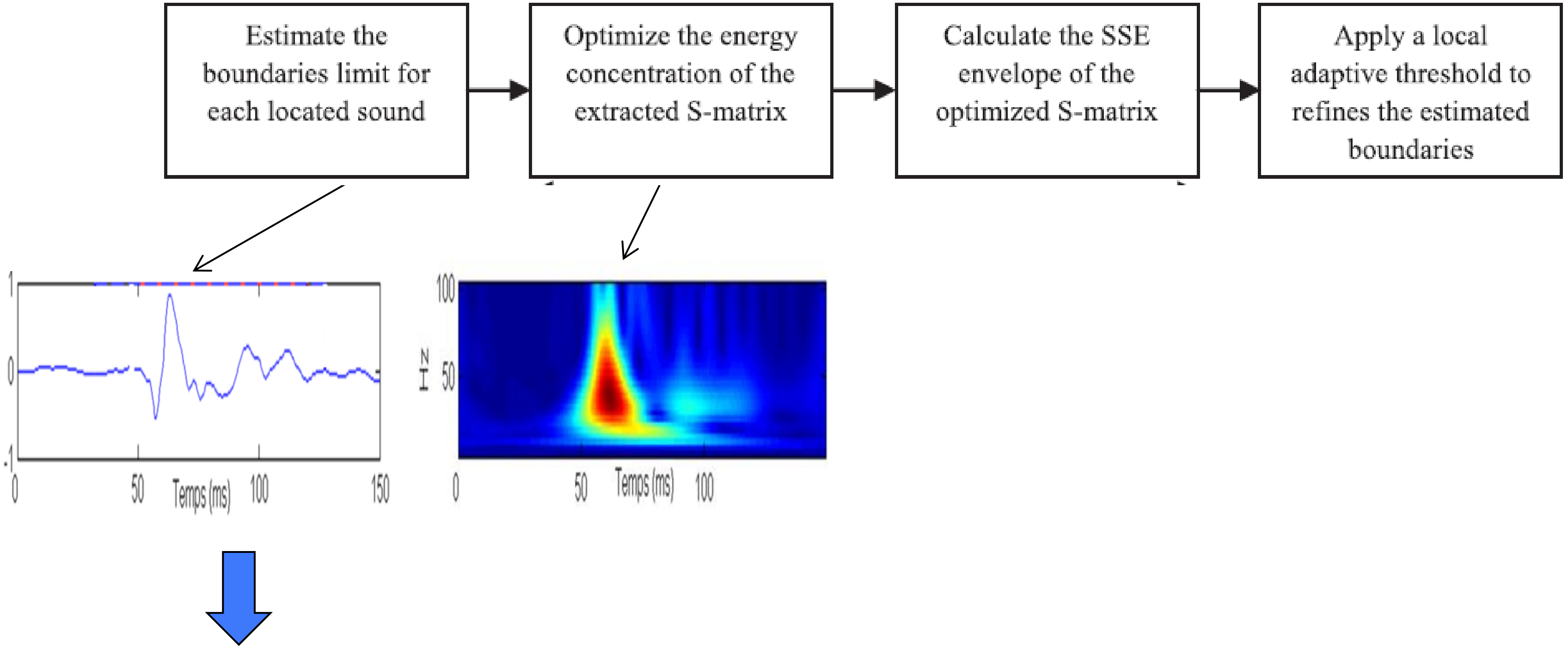
Ideal representations

S-Transform



OSSE method

The OSSE algorithm is applied on each extracted sound of the PCG signal



150ms centered windows

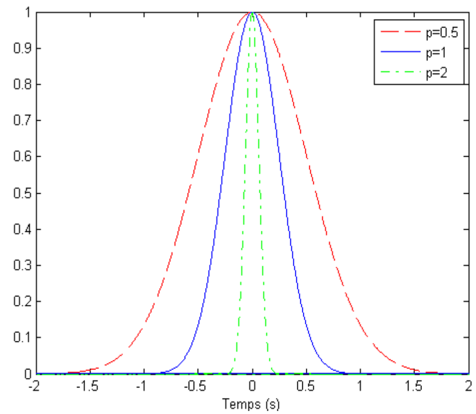
A. Moukadem, A. Dieterlen, C. Brandt, A Robust Heart Sound Segmentation Module Based on S-Transform, *Biomedical Signal Processing and Control*, 10.1016/j.bspc.2012.11.008

S Transform Optimization

Gaussian windows with the parameter *p*:

$$g(t,\sigma)=\frac{1}{\sigma(f)\sqrt{2\pi}}e^{\frac{-t}{2\sigma(f)^2}} \qquad \sigma(f)=\frac{1}{|f|^{p}}$$

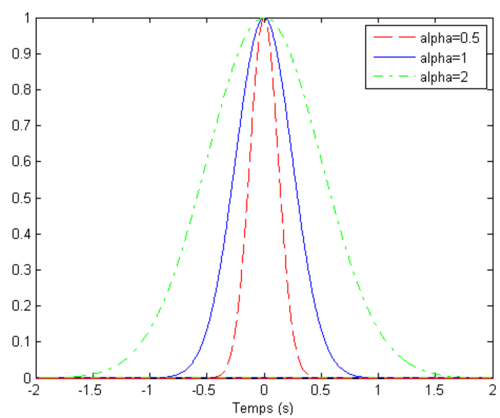
$$S^{p}(\tau,f)=\frac{|f|^{p}}{\sqrt{2\pi}}\int_{-\infty}^{+\infty}x(t)e^{\frac{-(t-\tau)^2 f^{2p}}{2}}e^{-i2\pi ft}dt$$



Gaussian windows with *α*:

$$\sigma(f)=\frac{\alpha}{|f|}$$

$$S^{\alpha}(\tau,f)=\frac{|f|}{\alpha\sqrt{2\pi}}\int_{-\infty}^{+\infty}x(t)e^{\frac{-(t-\tau)^2 f^2}{2\alpha^2}}e^{-i2\pi ft}dt$$



Optimization algorithm [Sejdic07]:

- p (or α) between 0.5 and 2 with a step of 0.1 => $S_x^{\alpha}(t,f)$
- Normalization:

$$\overline{S_x^{\alpha}(t,f)}=\frac{S_x^{\alpha}(t,f)}{\sqrt{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}|S_x^{\alpha}(t,f)|^2\,dtdf}}$$

- Energy concentration measure:

$$CM(\alpha)=\frac{1}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left|\overline{S_x^{\alpha}(t,f)}\right|dtdf}$$

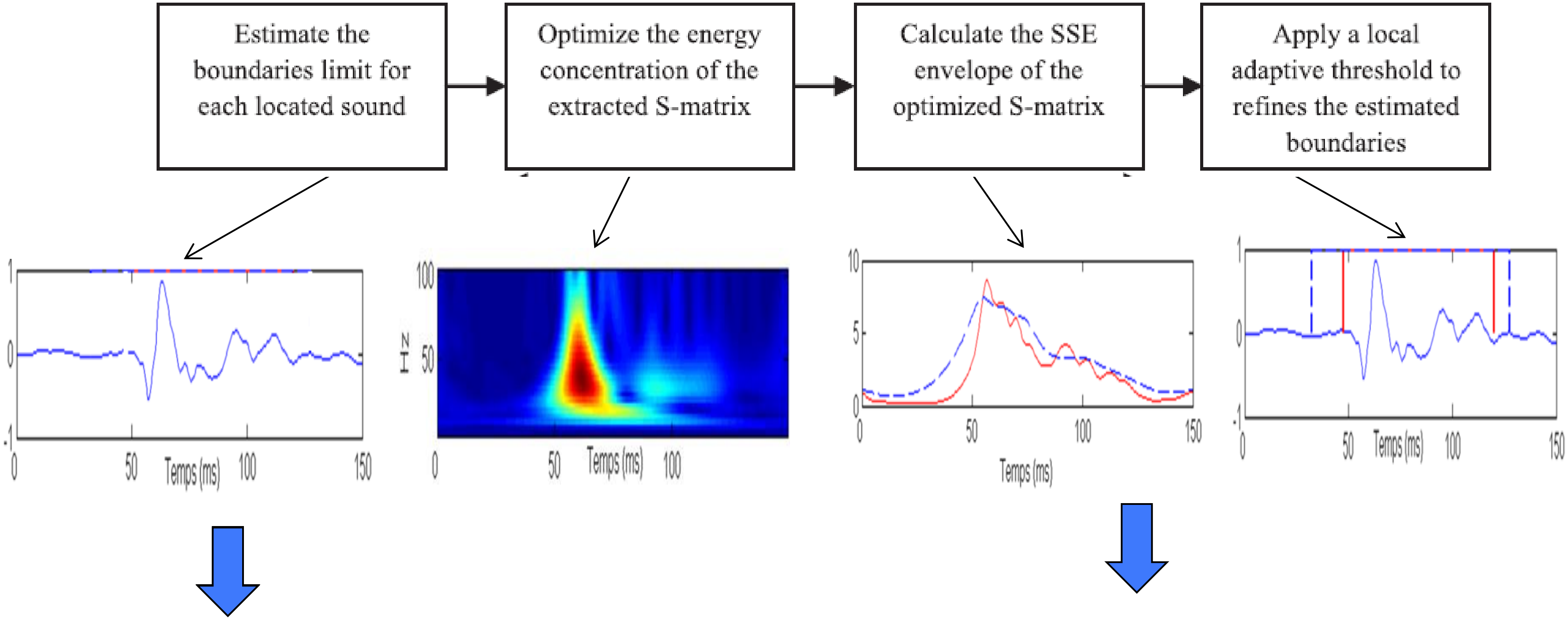
- Optimal α and S:

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

$$S_x^{\alpha}(t,f)=S_x^{\alpha_{opt}}(t,f)$$

OSSE method

The OSSE algorithm is applied on each extracted sound of the PCG signal



150ms centered windows

$$OSSE(t) = -\sum_{f=1}^{N} \left|S_{opt}(t, f)\right|^2 \log(\left|S_{opt}(t, f)\right|^2)$$

A. Moukadem, A. Dieterlen, C. Brandt, A Robust Heart Sound Segmentation Module Based on S-Transform, *Biomedical Signal Processing and Control*, 10.1016/j.bspc.2012.11.008

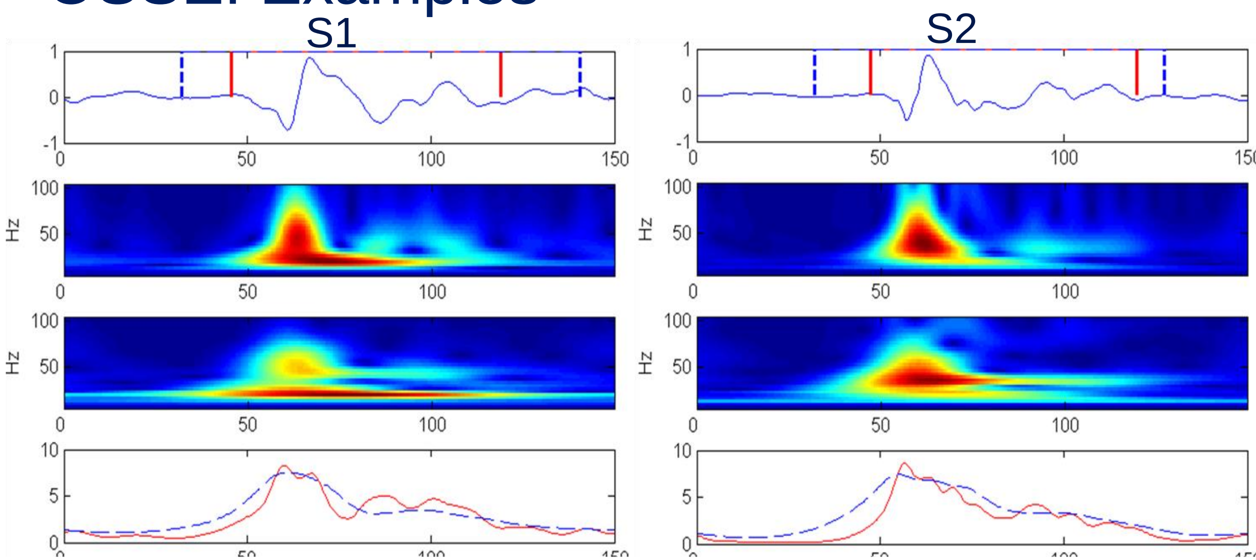
OSSE: Examples

Boundaries detection with and without optimization

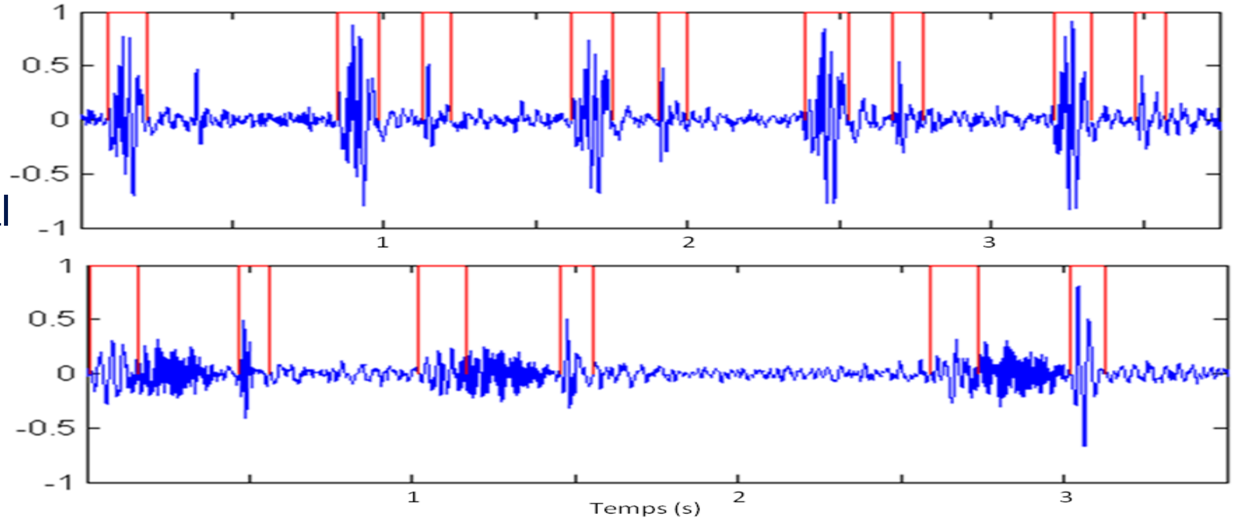
Optimized S-Transform

Classic S-Transform

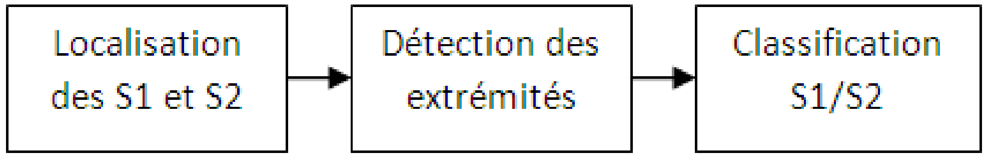
SSE and OSSE envelopes

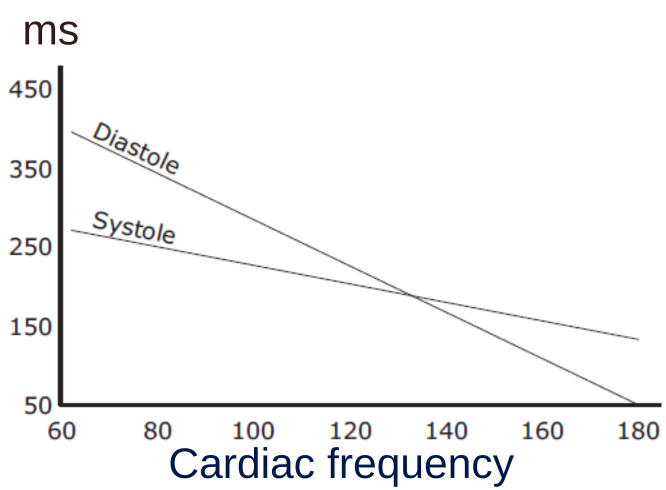


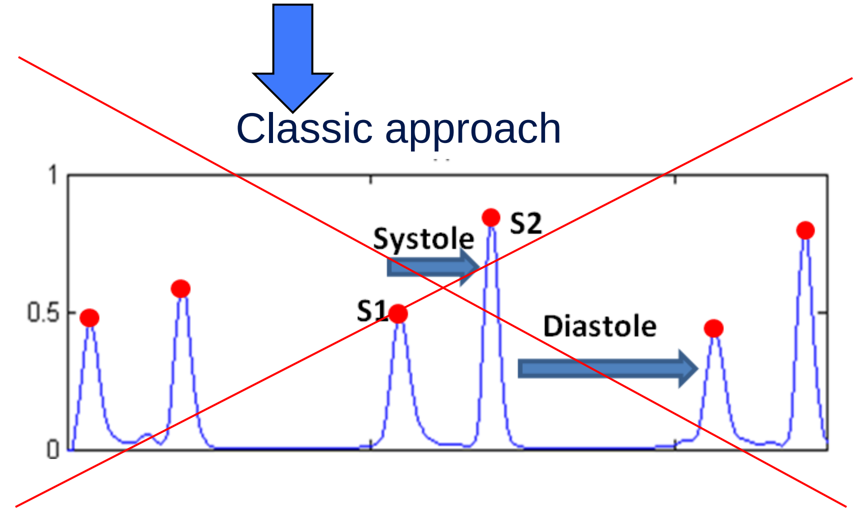
Boundaries detection for a normal and pathological heart sounds by using the OSSE method.



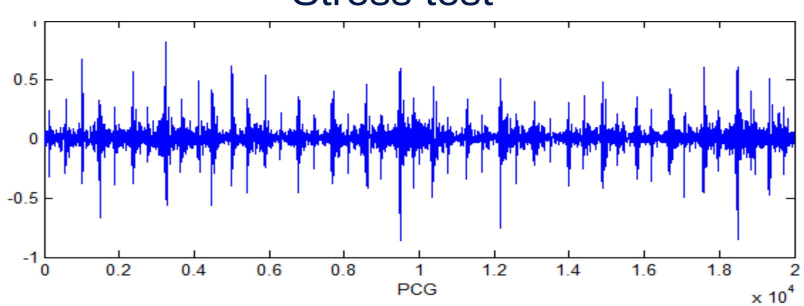
Problematic



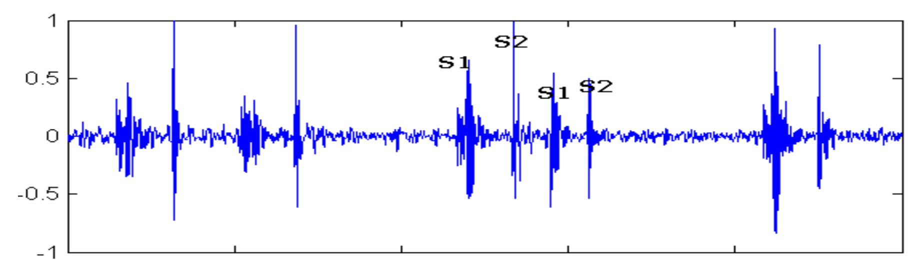




Stress test



Tachycardie



New features

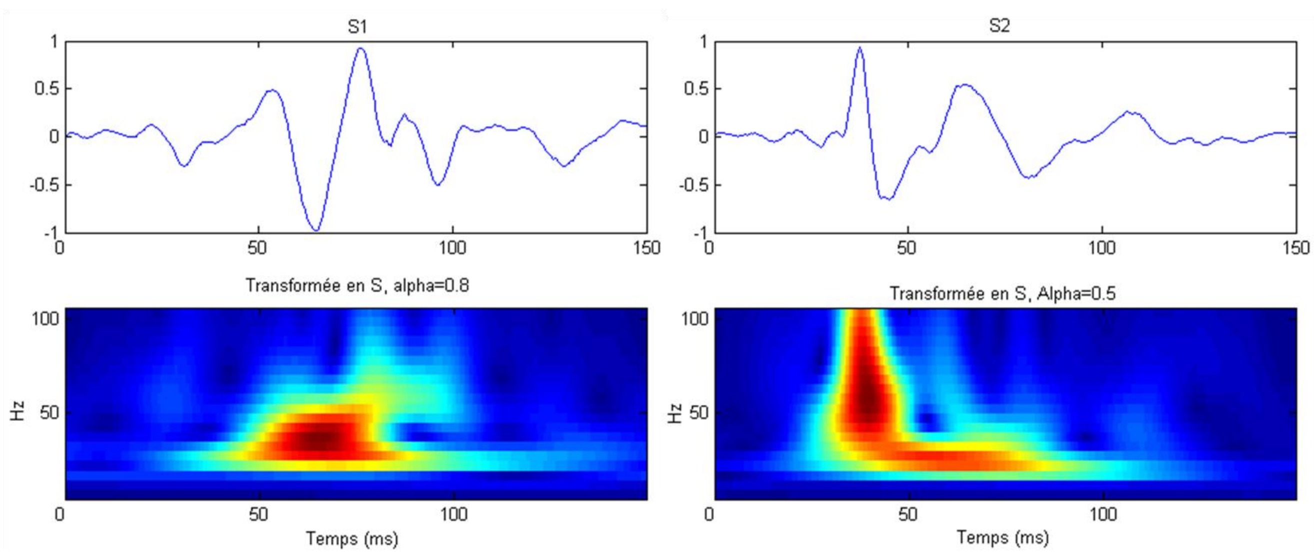
The parameters that control the width of the Gaussian window to optimize the energy concentration of the S-Transform.

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

$$\sigma(f) = \frac{\alpha}{|f|}$$

$$\sigma(f) = \frac{1}{|f|^p}$$

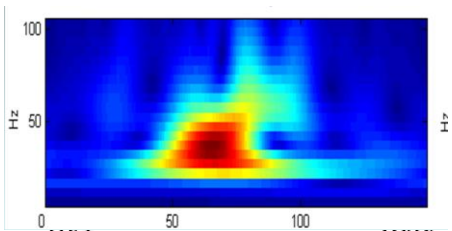
Optimize the energy concentration → Discriminate S1 et S2



Méthode S-SVD

Singular value decomposition of the S1 or S2 S-matrix :

$\hat{X}$



$m \times n$

S-matrix for a S1 or S2 sound

$$\approx U = \begin{pmatrix} u_{11} & \cdots & u_{1r} \\ \vdots & \ddots & \\ u_{m1} & & u_{mr} \end{pmatrix}_{m \times r} \quad S = \begin{pmatrix} s_{11} & 0 & \cdots \\ 0 & \ddots & \\ \vdots & & s_{rr} \end{pmatrix}_{r \times r} \quad V^{\mathsf{T}} = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \\ v_{r1} & & v_{rn} \end{pmatrix}_{r \times n}$$

Singular vectors
Time domain

Singular values

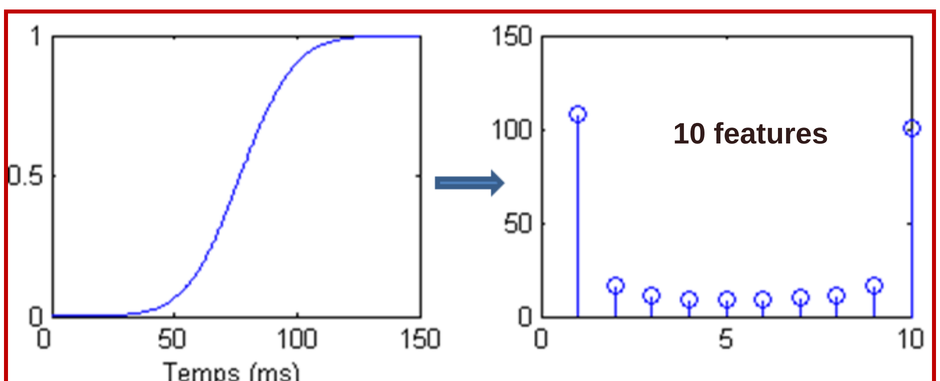
Singular vectors
Frequency domain

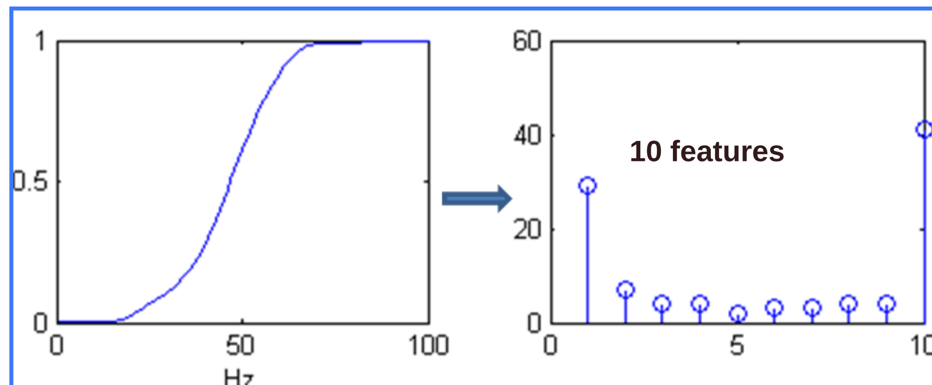
Orthonormal singular vectors ⟶ $f_{U1} = \{u_{11}^2, u_{12}^2, \ldots, u_{1m}^2\}$ Avec $\sum_{i=1}^{m} u_{1i}^2 = 1$

Probability density function: $F_{U1} = \{v_1, v_2, \ldots, v_m\}$ Avec $v_j = \sum_{i=1}^{j} u_{1i}^2$

[Hassanpour04]

The singular vectors that correspond to the higher singular values contain more information





The ST-Spectrogram and Cohen's Class

ST-Spectrogram:

$$|S_x(t,f)|^2 = \left| \int_{-\infty}^{+\infty} x(\tau) w(\tau - t) e^{-2\pi j f \tau} d\tau \right|^2$$

$$= S_x(t,f).S_x^*(t,f)$$

$$= \iint x(\tau) w(\tau - t) x^*(\tau) w^*(\tau - t') e^{-j2\pi f(\tau-\tau')} d\tau d\tau'$$

Cohen's class representation [Cheng Lui et al. 2010]:

$$= \iiint x(u + \frac{1}{2}t) x^*(u - \frac{1}{2}t) \phi(\theta, t, f) e^{-j\theta t} e^{-jtf} e^{iu\theta} du dt d\theta$$

Kernel function:

$$\phi(\theta, t, f) = e^{-j\pi t\theta} \int_{-\infty}^{+\infty} w(\frac{u}{f}) w^*(\frac{u-\theta}{f}) e^{j2\pi tu} du$$

Or time-lag kernel function:

$$\Phi(t,\tau,f) = f^2 \psi(f(-t + \frac{1}{2}\tau)) \psi^*(f(-t - \frac{1}{2}\tau)) = \Phi(t,\tau,f) = \frac{f^2}{2\pi} e^{-f^2(t^2 + \tau^2/4)}$$

In case of Gaussian windows

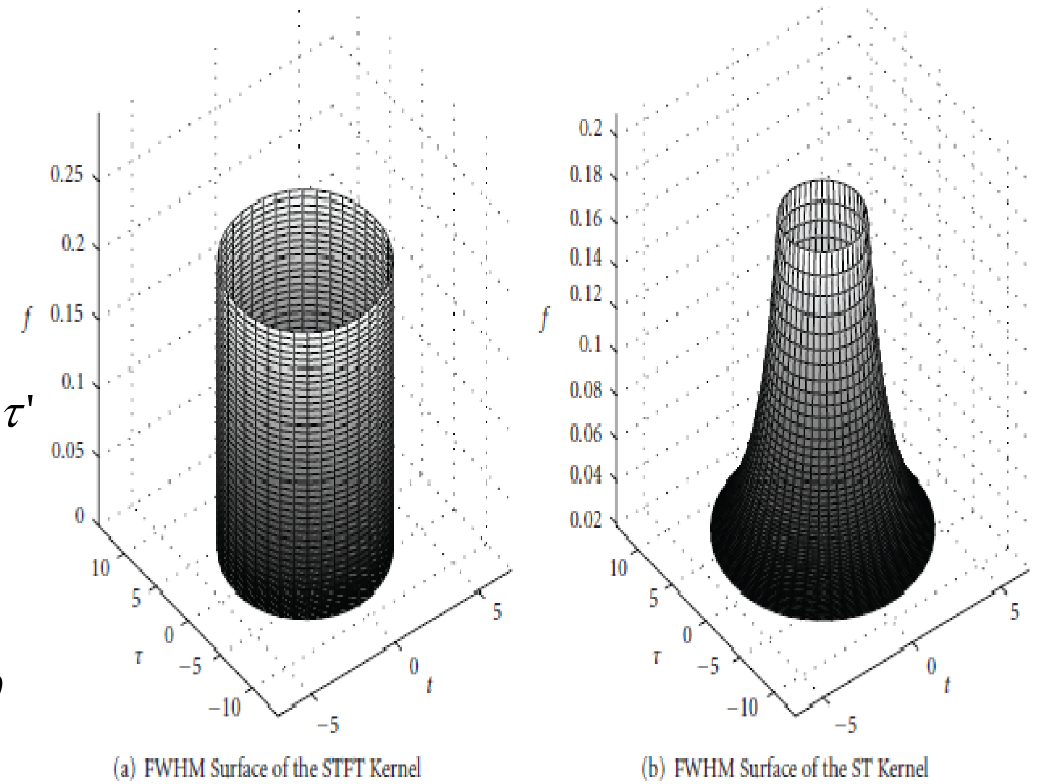


FIGURE 2: The surface of the time-lag kernel at the location of half maximum for (a) the GT- and (b) ST-spectrogram.

Extracted from [Cheng Lui et al. 2010]

Complexity measure via TF plane

The non-negativity property of the ST-Spectrogram:

$C_x(t,f) \geq 0$ $\Rightarrow$ Possibility to use the Shannon entropy measure: $H(C_x) = -\iint C_x(t,f)\log_2 C_x(t,f)dtdf$

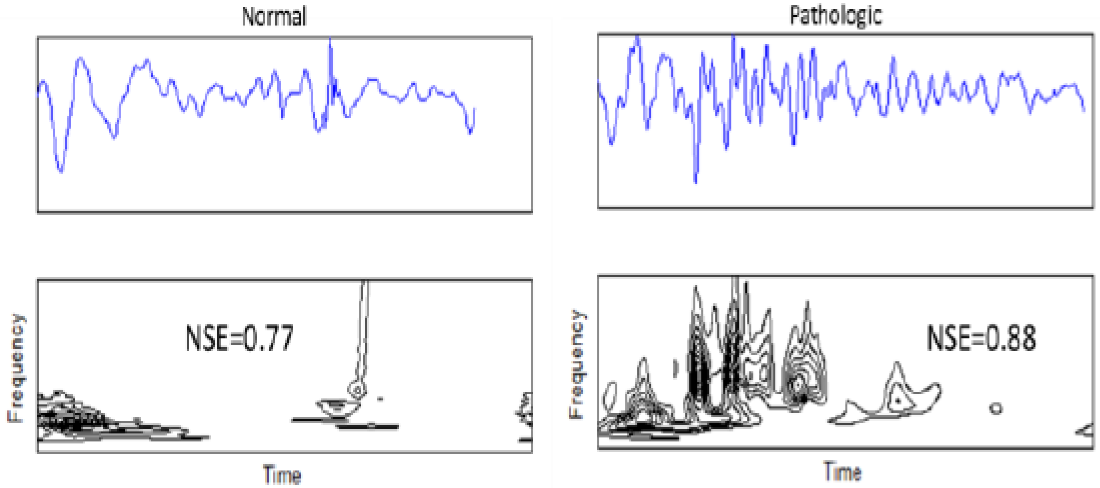
$$C_x^{norm}(t,f) = \frac{C_x(t,f)}{\iint C_x(u,v)dudv}$$

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

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

Normalized Shannon Entropy (NSE):

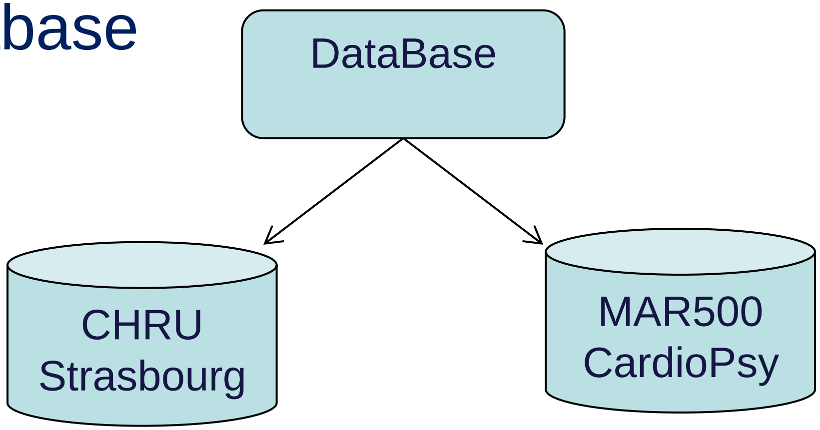
$$H_{norm}(C_x^{norm}) = \frac{H(C_x^{norm})}{\log_2(n \times m)}$$



Where, n is the samples number of the signal , m is the number of frequency voices used to calculate the ST-spectrogram

A. Moukadem, A. Dieterlen, et. al., Shannon entropy based on the S-Transform Spectrogram. Applied on the classification of heart sounds. IEEE Conference on Acoustics, Speech, and Signal Processing (ICASSP 2013), May 26-31, Vancouver, Canada.

Database



6 normal participants

Matériel:
- ➢Prototype
- ➢Format Wave, 8Khz (Stetho.exe).
- ➢Normalization

Base de Test:
- ➢40 Normal sounds(20 from MARS500 project)
- ➢40 pathologic sounds(CHRU)
- ➢66 subjects, 80 sounds
- ➢Validated by an experienced cardiologist

Localization results: comparative study

- 1539 Si (i=1et 2) from 66 subjects (80 sounds)
- Additional noise (3 Levels = 10, 5 et 0 dB)

Méthodes	SNR=10 dB		SNR=5 dB		SNR= 0 dB	
	Sens%	VPP%	Sens%	VPP%	Sens%	VPP%
Méthodes Temporelles						
Shannon	90	91	86	88	80	84
Méthodes Fréquentielles						
Hilbert	87	89	84	83	78	78
Homomorphique	91	90	88	89	86	83
CSCW	92	92	89	89	84	83
Multi-échelles	90	**98**	88	**93**	86	87
Méthodes Non-linéaires						
Entropie	91	92	88	88	85	84
VFD	88	90	85	87	82	85
Simplicité	**94**	**96**	92	92	85	84
Méthodes Proposées						
RBF	91	91	86	87	75	78
SRBF	92	**98**	91	**93**	87	**89**
SSE	**96**	95	93	**94**	**88**	**89**

Robustuness against noise

A. Moukadem, Ph.D thesis, "Segmentation et classification des signaux non-statonnaires. Application au traitement des sons cardiaques et à l'aide au diagnostic.", UHA, Mulhouse, France

Segmentation: The OSSE method

Energy concentration of different Gaussian windows

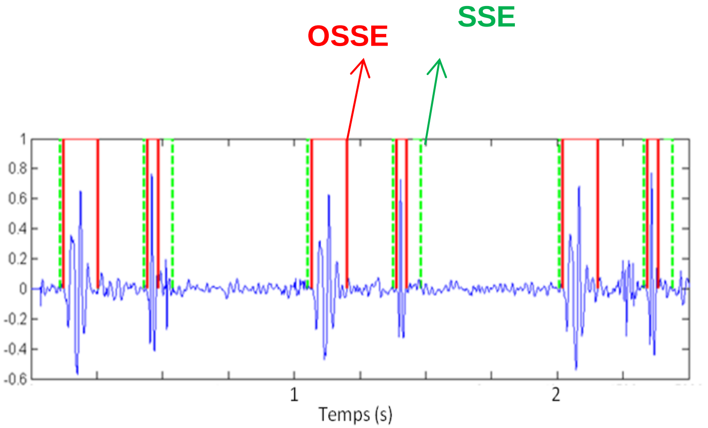
S-Transform	α_{opt}	$CM(\alpha_{opt})$	p_{opt}	$CM(p_{opt})$	$CM_{\alpha=1,p=1}$
S1	0.82±0.45	0.0185±0.0017	1.1±0.5	0.0186±0.0018	0.0177±0.0015
S2	0.55±0.3	0.0186±0.0015	1.37±0.5	0.0186±0.0018	0.0175±0.0014
Total	0.68±0.37	**0.0185±0.0016**	1.23±0.5	**0.0186±0.0018**	0.0176±0.0015

Comparaison of different TF transformations

TF	ST	$S_{\alpha opt}$	STFT	ASTFT
S1	0.0177±0.0015	0.0185±0.0017	0.0179±0.0018	0.0181±0.0015
S2	0.0175±0.0014	0.0186±0.0015	0.0182±0.0016	0.0183±0.0018
Total	0.0176±0.0015	**0.0186±0.0018**	0.0180±0.0017	0.0182±0.0017

Evaluation of the OSSE method

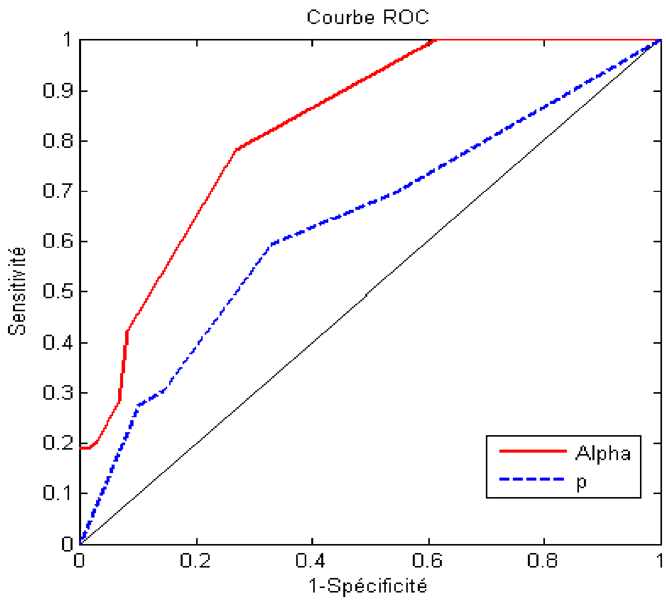
Méthodes	S1 (ms)			S2 (ms)		
	10dB	5dB	0dB	10dB	5dB	0dB
SSE	122.4±7.2	127.8±9.6	139.3±6	95.2±8.3	101.2±7.4	103.4±6.4
OSSE	110.7±4.32	113.6±6.5	137.1±5.3	69.1±5.4	77.9±8.2	94.2±4.7
Référence		**105.8±6**			**74.8±5.65**	



S1 and S2 classification results

Singular features

➢For each subject of the database we have one optimal **parameter α and p** (160 values in total for each parameter).



Receiver Operating Curve (ROC)
Area Under Curve (AUC)

AUC (α)=0.84
AUC (p)=0.64

α new accurate feature

Features vector

➢Sounds are segmented automatically**(OSSE).**

➢The average of the vectors features of each subject is calculated

➢One feature vector for S1 and one feature vector for S2 per subject.

➢KNN classifier and cross validation 5-blocks

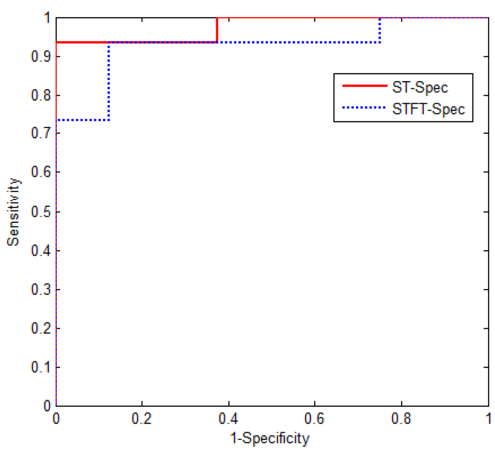
K-NN	Sensitivité	Spécificité	CR
		S-SVD	
T-Features	92%	92%	92%
F-Features	81%	88%	84%
SV-Features	60%	65%	62%
TF-Features	**95%**	**97%**	**96%**

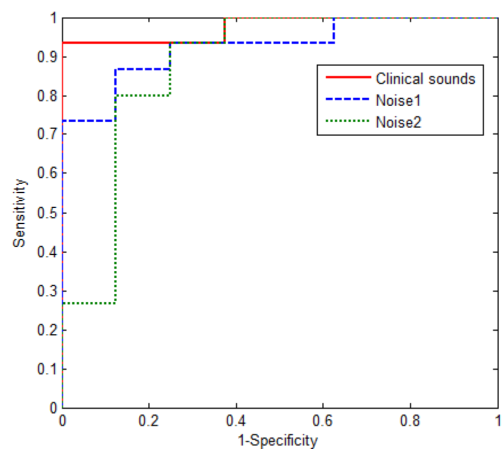
A. Moukadem, A. Dieterlen, C. Brandt "Study of two feature extraction methods to distinguish between the first and the second heart sounds", International conference on Bio-inspired systems and Signal processing, 1-4 February 2012, Algarve, Portugal.

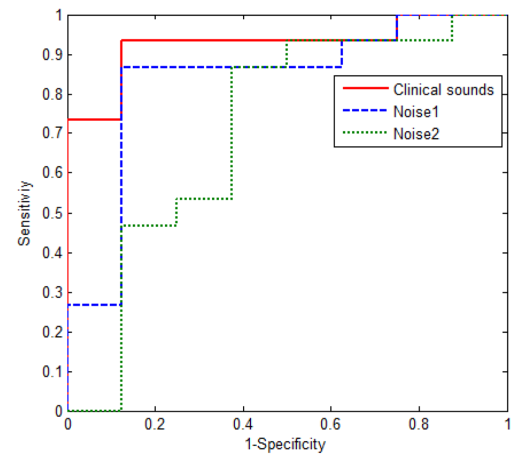
Murmur detection Results

Table 1: Shows the variation of AUC against white additive noise for the ST and the STFT spectrograms.

Spectrogram	AUC1	AUC2	AUC3
ST	**0.98**	**0.93**	**0.88**
STFT	0.93	0.84	0.7







A. Moukadem, A. Dieterlen, et. al., Shannon entropy based on the S-Transform Spectrogram. Applied on the classification of heart sounds. IEEE Conference on Acoustics, Speech, and Signal Processing (ICASSP 2013), May 26-31, Vancouver, Canada.

Conclusion and Future work

Robust and original heart sounds analysis module:

- ✓ Localization and segmentation methods.
- ✓ Validation of new features to classify S1 and S2.
- ✓ Validation of new feature to estimate the complexity of the signal via TFR (murmur detection).

- ➢ Theoretical enhancement of the S-transform, most notably enhancement of the energy concentration.
- ➢ Phase information provided by the S-Transform => feature extraction process.
- ➢ New campaign to collect signals with the E-care project in the University Hospital of Strasbourg is in motion.

- For the thesis
  - C. Brandt
  - R. Charles

Région Alsace

Les Hôpitaux Universitaires de STRASBOURG

mips LAB.EL

- For the Post-Doc

GROUPE Caisse des Dépôts Investissements d'Avenir Développement de l'Economie Numérique

On ne voit bien qu'avec le cœur...L'essentiel est invisible pour les yeux (le petit prince, chapitre 21).

You can only see with the heart... What is essential is invisible to the eye

Thanks for your attention!