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► **To cite this version:**

Blaise Kévin Guépié, B. Sciolla, Fabien Millioz, R. Ramassamy, E. Pinatel, et al.. Time-frequency Blood Flow Parameters Estimation for Micro-emboli Detection. IEEE ISPA, 2015, Zagreb, Croatia. pp. 66-71. hal-01917475

**HAL Id: hal-01917475**

**<https://hal.science/hal-01917475>**

Submitted on 2 Jul 2024

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# Time-frequency Blood Flow Parameters Estimation for Micro-emboli Detection

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**Abstract**—Detecting micro-emboli in the middle cerebral artery is a major challenge because these micro-emboli are related to the risk of stroke (cerebrovascular accident). Because micro-emboli are defined as High Intensity Transient Signals (HITS), their detection require the estimation of blood flow background signal ; i.e, the reference from which HITS have to be detected. In this paper, we propose an original procedure composed of two steps. Firstly, the background noise is isolated from the blood flow time-frequency image thanks to the log-likelihood segmentation method. Secondly, HITS detection threshold is calculated from a blood flow statistic using the spectral kurtosis approach. Our procedure is used on the transcranial Doppler data from two patients and the results show that the mean percentage error of the velocity envelope estimation is reduced from 5% to 3% and 92% of micro-emboli are counted as detected HITS.

## I. INTRODUCTION

Micro-emboli detection is a major challenge in medical area because they are related to the risk of cerebrovascular accidents (stroke) [1]. Reliably detect micro-emboli is then an essential step in order to make appropriate patient-management decisions.

The transcranial Doppler is a non invasive system traditionally used to monitor the middle cerebral artery and to potentially detect micro-emboli [2].

Several methods have been proposed to reliably identify micro-emboli from the transcranial Doppler signal. Most of them are based on signal processing approach. The underlying idea of this method is to define a statistic parameter and an associated threshold for which there is an equivalence between any value of this parameter exceeding the threshold and the presence of micro-emboli [3].

In [3], [4], [5], some micro-emboli detectors are proposed from signal time series model or from cardiac cycle energy model. However, because micro-emboli are defined as High Intensity Transient Signals (HITS), their detection required the blood flow background signal estimation; i.e, the reference from which HITS have to be detected. To the best of our knowledge, this tricky problem is avoided in most papers and the blood flow background signal amplitude is not clearly estimated. Most of the time it is overestimated because the mean amplitude is used and it contains some HITS.

In this paper, we propose an original procedure based on an image processing approach for detecting HITS. It is composed of two main steps. Firstly, the log-likelihood segmentation method is used on time-frequency image for determining the velocity envelope, i.e the maximum instantaneous velocity in order to extract the portion of image which contains the blood flow. Secondly, a statistic approach with the spectral kurtosis parameter is applied on the extracted portion of image and a threshold is calculated for HITS detection. The advantage of this procedure is related to the fact that it does not explicitly need the knowledge of the blood flow background signal for HITS detection. Thus, in contrast to the other methods found in the literature, HITS are firstly detected and then the blood flow background signal is estimated without HITS; this avoids blood flow background signal overestimation. This background signal estimation is necessary for separating micro-emboli and artifacts insofar micro-emboli are defined as HITS of 3 dB higher than this background signal [6].

The paper is organized as follows. Section II gives some explanations of transcranial Doppler and the problem statement. Section III presents the procedure for determining the envelope velocity and detecting the High Intensity Transient Signals. Some conclusions are drawn in Section V.

## II. MATERIAL AND PROBLEM STATEMENT

### A. Material

The Doppler effect reflects the frequency change of an ultrasonic wave reflected by a moving target. The target velocity is calculated by the expression [7] :

$$v = \frac{f_D c}{2f_0 \cos(\theta_D)} \quad (1)$$

where  $f_D$  is the Doppler shift frequency,  $f_0$  is the frequency of emitted wave,  $c$  is the speed of sound and  $\theta_D$  is the angle between insonation direction and target motion direction.

The transcranial Doppler is generally used for detecting micro-emboli based on the Doppler effect. The blood flow velocity is evaluated from an ultrasound system. The monitoring needs the insonation of the middle cerebral artery by an ultrasound beam emitted through a thin region of bone above the ear (the temporal window) [2]. The emitted waves have

a central frequency between 1.5 and 2 MHz and they last 10  $\mu s$ . The pulse repetition frequency (PRF) is between 4 and 12 kHz. From a selected depth, reflected ultrasound signals are demodulated at the emitted signal frequency by a quadrature modulation in order to obtain the complex Doppler signal.

### B. Problem statement

The exact definition of micro-emboli is not yet known. However, the 9<sup>th</sup> international conference of cerebral hemodynamics published some of micro-emboli characteristics [6]:

- the duration of micro-embolic signals is lower than 300 ms;
- signal amplitude is 3 dB higher than the blood flow background signal;
- the velocity is unidirectional in the Doppler sonogram;
- the audio signal is characteristic.

Here we are interested to investigate the sentence “signal amplitude is 3 dB higher than the blood flow background signal” because in our advice, it is the most difficult condition to be observed.

Indeed, the detection of micro-emboli which also are HITS requires the knowledge of the blood flow background signal. Likewise, to know the blood flow background signal, HITS(micro-emboli and artifacts) have firstly to be detected and removed from the same signal. This shows the difficulty to extract the blood flow background signal. Most papers in literature achieve the estimation of the blood flow background signal including HITS. It follows that the background signal is overestimated and some HITS and likely some micro-emboli detection is missed.

## III. PROPOSED METHOD

### A. Procedure description

The major steps of our proposed method are the following

- Determining the velocity envelope also called the maximum instantaneous velocity.
- Removing the data above the velocity envelope and below the null velocity.
- Calculating the HITS detection threshold on the remaining data (or portion of the image).
- Detecting HITS by using the previous threshold.

### B. Estimation of the velocity envelope

This paragraph is devoted to the estimation of the maximum instantaneous velocity in time-frequency domain also called the velocity envelope. This step is essential in order to achieve a correct detection of HITS in subsection III-C.

In this paper, the time-frequency image is obtained by applying the Short Time Fourier Transform (STFT) on the complex transcranial Doppler signal. Lin et al.[7] use Otsu segmentation method [8] on time-frequency image for detecting the velocity envelope. However, unlike Lin et al. method, our segmentation approach is based on the log-likelihood method which is briefly explained as follows. Let us set  $\Omega$  the time-frequency image or the spectrogram of the transcranial Doppler signal. The segmentation of  $\Omega$  into two separate areas

$\Omega_0$  and  $\Omega_1$  such as  $\Omega = \Omega_0 \cup \Omega_1$  can be done by testing two statistical hypotheses. Let  $N$ ,  $\mathcal{C}$  and  $x$  respectively be the total number of pixels in  $\Omega$ , the boundary between  $\Omega_0$  and  $\Omega_1$  and the number of pixels in  $\Omega_0$  corresponding to the fixed boundary. Let also  $(Y_i)_{1 \leq i \leq N}$  be the sequence of independent random variables generating pixel values  $(y_i)_{1 \leq i \leq N}$ . The two statistical hypotheses to test are

$$\begin{aligned} \mathcal{H}_0 &= \{Y_1 \sim \mathcal{P}_0, \dots, Y_N \sim \mathcal{P}_0\} \\ &\text{vs} \\ \mathcal{H}_1 &= \{Y_1 \sim \mathcal{P}_0, \dots, Y_x \sim \mathcal{P}_0, Y_{x+1} \sim \mathcal{P}_1, \dots, Y_N \sim \mathcal{P}_1\}, \end{aligned} \quad (2)$$

where  $\mathcal{P}_i$ ,  $0 \leq i \leq 1$  are two different cumulative distribution functions (cdf). The hypothesis  $\mathcal{H}_0$  supposes that all pixels derive from a common law  $\mathcal{P}_0$  and  $\mathcal{H}_1$  supposes that pixels of region  $\Omega_0$  and  $\Omega_1$  derive from two distinct laws  $\mathcal{P}_0$  and  $\mathcal{P}_1$ . The log-likelihood ratio  $LL$  is defined by

$$LL(x) = \ln \left( \frac{\prod_{i=1}^x f_0(y_i) \prod_{i=x+1}^N f_1(y_i)}{\prod_{i=1}^N f_0(y_i)} \right), \quad (3)$$

where  $f_i$  is the probability density function of  $\mathcal{P}_i$  for  $i \in \{0, 1\}$ . In practice, the probability density functions  $f_0$  and  $f_1$  are unknown and computed using Parzen estimates on the data.

The value of  $LL$  depends on the number of pixels belonging to  $\Omega_0$  and thus, it also depends on  $\mathcal{C}$  the boundary between  $\Omega_0$  and  $\Omega_1$ . The idea of using the  $LL$  is that  $LL$  increases as the current position of boundary  $\mathcal{C}_c$  is close to the true position  $\mathcal{C}_T$ . The log likelihood ratio  $LL$  is maximum when  $\mathcal{C}_c = \mathcal{C}_T$ . Because the denominator of (3) does not depend on the boundary (or  $x$ ), it will not be considered during the minimization. Thus, the function to minimize becomes

$$LL_2(x) = -\ln \left( \prod_{i=1}^x f_0(y_i) \prod_{i=x+1}^N f_1(y_i) \right).$$

The segmentation can be done by initializing a boundary and optimizing each individual  $y_i \in \mathcal{C}$  recursively. However, this methods needs large computational time. In practice, the contour is build column by column and in order to smooth it, a smoothing term or regularization term is added to  $LL_2$  before optimization. This smoothing term is proportional to the length of the boundary [9]:

$$\alpha \sqrt{1 + (y_{i_p} - y_{i_x})^2},$$

where  $y_{i_p}$  is the previous determined pixel belonging to the boundary,  $y_{i_x}$  is the current boundary pixel and  $\alpha$  is a tuning parameter.

In summary, our boundary determination method is recursive and given by

$$\mathcal{C} = \left\{ (y_{i_x})_{i=1}^{N_c} / \hat{x} = \arg \min_x LL_2(x) + \alpha \sqrt{1 + (y_{i_p} - y_{i_x})^2} \right\}, \quad (4)$$

where  $N_c$  is the image number of columns.

### C. Detection of High Intensity Transient Signals

Micro-emboli are defined as High Intensity Transient Signals (HITS). The detection of HITS is tricky because it requires the knowledge of the blood flow background signal, i.e, the blood flow acquired in absence of HITS. The main difficulty is how to know whether the considered signal (or a portion) does not contain any HITS ?

To avoid this difficulty, a spectral kurtosis approach [10] is used on the selected part of the time-frequency image (i.e, below the velocity envelope and with positive frequency or velocity). Under some assumptions, the spectral kurtosis approach can separate HITS and the blood flow background signal. Let us briefly recall the spectral kurtosis approach.

Let us assume that the STFT model of blood flow Doppler signal (without HITS) in the selected part of the time-frequency image is

$$s(n, k) = \xi(n, k), \quad (5)$$

where  $n$  and  $k$  are respectively time and frequency indexes,  $(\xi(n, k))_{n \geq 1, k \geq 1}$  is a sequence of independent identically distributed (i.i.d) circular complex Gaussian variables with zero mean and unknown variance  $\sigma^2$ , and the STFT model of blood flow Doppler signal in the selected image part when HITS arise is

$$s(n, k) = \gamma(n, k) + \xi(n, k), \quad (6)$$

where  $\gamma(n, k)$  is a deterministic complex value.

The HITS are of short duration with respect to acquired Doppler signal. This implies that  $\gamma(n, k) = 0$  for the most value of  $(n, k)$ . Thus, the smallest values of  $s(n, k)$  have the same distribution than those of  $\xi(n, k)$ .

Moreover, when an energy detector is used to detect HITS, thresholding the energy means thresholding the spectrogram. Removing points greater than the threshold gives a truncated complex Gaussian variable [10]. A circular complex variable  $Z = A + iB$  of zero mean and  $\sigma^2$  variance has the probability density function independent from the phase:

$$f_\sigma(\rho) = \frac{2\rho}{\sigma^2} \exp\left\{\frac{-\rho^2}{\sigma^2}\right\}, \quad (7)$$

where  $\rho = \sqrt{a^2 + b^2}$ . When this circular complex Gaussian variable is truncated by the threshold  $h$ , the probability density function  $f_{\sigma,h}$ , the variance  $Var_{\sigma,h}$  and the spectral kurtosis  $SK_{\sigma,h}$  are respectively [10]

$$f_{\sigma,h}(\rho) = \begin{cases} \frac{2}{1 - \exp\left\{-\frac{h^2}{\sigma^2}\right\}} \frac{\rho}{\sigma^2} \exp\left\{\frac{-\rho^2}{\sigma^2}\right\} & \text{for } 0 \leq h \leq \rho \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

$$Var_{\sigma,h} = \sigma^2 \left(1 - \frac{(h/\sigma)^2}{\exp\{(h/\sigma)^2\} - 1}\right), \quad (9)$$

$$SK_{\sigma,h} = \frac{(\exp\{(h/\sigma)^2\} - 1) (2(h/\sigma)^2 - (h/\sigma)^4) - 2(h/\sigma)^4}{(\exp\{(h/\sigma)^2\} - 1 - (h/\sigma)^2)^2}. \quad (10)$$

From (10), it is clear that the spectral kurtosis depends only on the normalized threshold  $(h/\sigma)$  and  $SK$  is an invertible (continuous non-decreasing) function. So, there is an unique  $h_n(\kappa)$  such as

$$SK_{1,h_n(\kappa)} = \kappa. \quad (11)$$

The value of  $h_n(\kappa)$  is approximated by numerically inverting (10). On the other hand, using the STFT, it is possible to find the non-normalized threshold  $h(\kappa)$  such as the spectral kurtosis of the points smaller than the threshold is equal to a value  $\kappa$

$$SK_{\sigma,h(\kappa)} = \kappa. \quad (12)$$

The noise variance estimator  $\hat{\sigma}_\kappa^2$  is then

$$\hat{\sigma}_\kappa^2 = \left(\frac{h(\kappa)}{h_n(\kappa)}\right)^2. \quad (13)$$

The noise variance estimator depends on  $\kappa$ . Empirically, the value of  $\hat{\sigma}_\kappa^2$  for  $\kappa = (-0.3)$  has been found to be the most relevant [10].

The HITS are then detected as the points (or pixels) whose STFT squared modulus exceeds the threshold  $h_H$  given by the uniformly most powerful test [11]:

$$h_H = \hat{\sigma}_{-0.3}^2 \ln\left\{p_{fa}^{-1}\right\}, \quad (14)$$

where  $p_{fa}$  is the prescribed false alarm probability.

## IV. EXPERIMENTAL RESULTS

In this section, we evaluate the accuracy of our estimated parameters as well as the performance of detection. Two patients are monitored by the TCD-X of Atys Medical which is a transcranial Doppler portable device. Micro-emboli of both patients are detected by medical experts and this micro-emboli detection serves as a reference for evaluation. The duration signal of patient  $n^\circ 1$  is 497s and medical experts detect 16 micro-emboli. The duration signal of patient  $n^\circ 2$  is 303s and medical experts detect 36 micro-emboli.

### A. Accuracy of the velocity envelope

The accuracy of the velocity envelope determination is investigated here. Two time-frequency images coming from two patients are used. These images are obtained by the spectrogram of the transcranial Doppler signal. On both images, ground truth envelopes are drawn by an expert and serve as reference. Our envelope results is compared to those of Otsu used by Lin et al. in [7] through the ground truth. The selected regularization factor is  $\alpha = 0.25$ .

Let  $\mathcal{C}_E = \{y_i^E, 1 \leq i \leq N_c\}$ ,  $\mathcal{C}_L = \{y_i^L, 1 \leq i \leq N_c\}$  and  $\mathcal{C}_O = \{y_i^O, 1 \leq i \leq N_c\}$  be respectively the ground truth, the envelope obtained by the Otsu method and the envelope

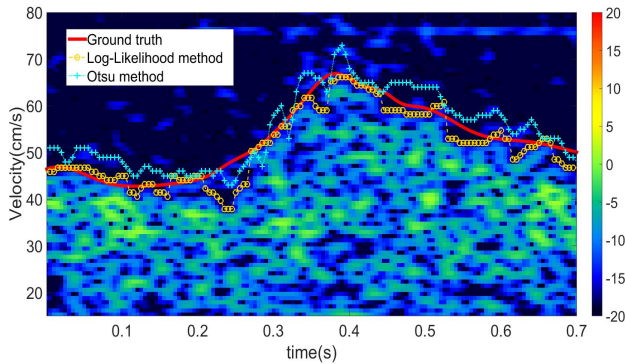


Fig. 1. Comparison of velocity envelopes for low noise.

TABLE I  
ERRORS OF VELOCITY ENVELOPES FOR LOW NOISE.

Errors	Methods	
	Otsu	log-likelihood
Mean percentage	5.57%	3.71 %
Mean least squares	13.83	9.74

obtained by the log-likelihood method. The comparison is done by calculating two quantities. The first one is the mean percentage error:

$$err_{mp} = \frac{1}{N_c y_i^E} \sum_{i=1}^{N_c} |y_i^l - y_i^E|, l \in \{L, O\}, \quad (15)$$

and the second one is the mean least squares error:

$$err_{mfs} = \frac{1}{N_c} \sum_{i=1}^{N_c} |y_i^l - y_i^E|^2, l \in \{L, O\}. \quad (16)$$

Figure 1 shows the comparison of velocity envelope estimation between the Otsu method and our proposed log-likelihood method. Both the methods envelopes are visually close to the ground truth and the log-likelihood method seems to be the best. Table I shows that the mean percentage error is small for both the methods comparatively to the ground truth; in other words, both the methods give reliable envelopes. The mean squares errors of Table I also shows that an improvement of approximately 2% is achieved for the velocity envelope determination. So, our proposed log-likelihood method is better than the Otsu method for the velocity envelope determination.

### B. Performance of HITS detection

The procedure of micro-emboli detection is hierarchical. Firstly, HITS are detected by using the spectral kurtosis approach. Then, HITS are separated between micro-emboli and artifacts. In this paper the discrimination between micro-emboli and artifact is not investigated and the HITS detection performance is related to the percentage of micro-emboli belonging to the detected HITS.

Figure 2 show an example of time-frequency image where the velocity envelope is determined and the portion of image

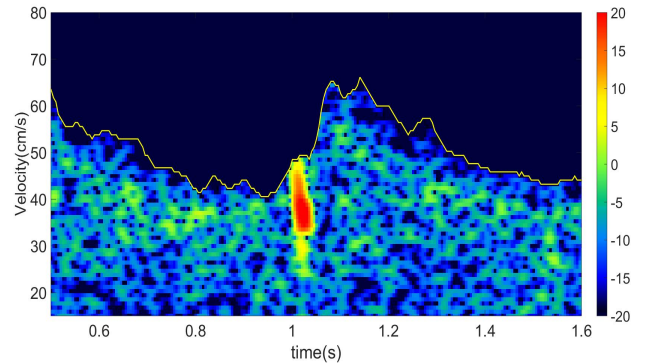


Fig. 2. An example of time-frequency image before HITS detection.

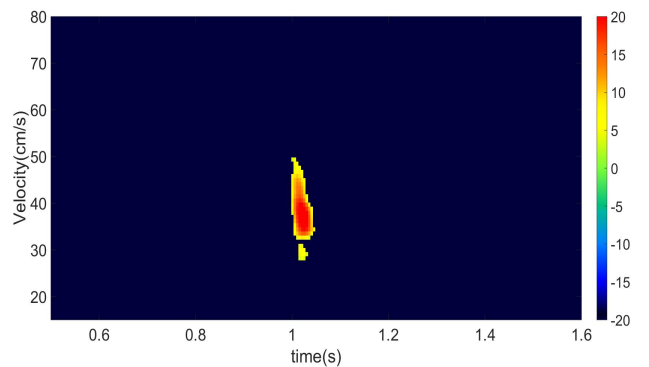


Fig. 3. An example of HITS detection by the spectral kurtosis approach.

TABLE II  
PERFORMANCE OF HITS DETECTION BY THE SPECTRAL KURTOSIS APPROACH.

Patients	$n^{\circ}1$	$n^{\circ}2$
Total number of micro-emboli	16	36
Number of micro-emboli counted as HITS	13	35
Percentage of micro-emboli counted as HITS	81.25%	97.22%

above the velocity envelope as well as the negative velocity are removed. The remaining image previously called the selected image part is used for HITS detection by the spectral kurtosis approach.

The experimentation parameters are the following. The prescribed false alarm rate is  $p_{fa} = 5 \times 10^{-2}$  and the HITS detection windows are not overlapped of size 300s.

Figure 3 shows an example of HITS detected and segmented. According to this picture, the detection seems to be efficient.

Table II shows the results of HITS detection using our procedure. The global percentage of micro-emboli counted as HITS is equal to 92,31%. These results are encouraging and support the use of this method as a first step to micro-emboli detection.

## V. CONCLUSION

This paper addresses the problem of the time-frequency blood flow parameters estimation for micro-emboli detec-

tion. The velocity envelope is firstly determined in the time-frequency image. This envelope divides the image between a noised part and the selected part. The spectral kurtosis approach is then applied on the selected image part and HITS are detected followed by the estimation of the blood flow background signal magnitude which is required before the detection of micro-emboli. The first results show that the mean percentage error of the velocity envelope estimation is reduced from 5% to 3% and 92% of micro-emboli are counted as detected HITS. This result is encouraging and can serve as a basis for a future work concerning the separation between artifacts and micro-emboli.

#### ACKNOWLEDGMENT

This work was funded by the ANR-13-LAB3-0006-01 Lab-Com AtysCrea and was supported by the LABEX CeLyA (ANR-10-LABX-0060) of Universit de Lyon, within the program "Investissements d'Avenir" (ANR-11-IDEX-0007) operated by the French National Research Agency (ANR).

#### REFERENCES

- [1] P. Kahlert, F. Al-Rashid, P. Döttger, K. Mori, B. Plicht, D. Wendt, L. Bergmann, E. Kottenberg, M. Schlamann, P. Mummel *et al.*, "Cerebral embolization during transcatheter aortic valve implantation: A transcranial doppler study," *Circulation*, vol. 126, no. 10, pp. 1245–1255, 2012.
- [2] A. D. Mackinnon, R. Aaslid, and H. S. Markus, "Long-term ambulatory monitoring for cerebral emboli using transcranial doppler ultrasound," *Stroke*, vol. 35, no. 1, pp. 73–78, 2004. [Online]. Available: <http://stroke.ahajournals.org/content/35/1/73.abstract>
- [3] J.-M. Girault, S. Ménigot, and B. Guibert, "Dtection automatique de micro-emboles crbraux grce un nouveau dcteur de variance conditionnelle," *IRBM*, vol. 33, no. 3, pp. 217 – 222, 2012. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S1959031812000619>
- [4] S. Menigot, L. Dreibine, N. Meziati, and J. Girault, "Automatic detection of microemboli by means of a synchronous linear prediction technique," in *Ultrasonics Symposium (IUS), 2009 IEEE International*, Sept 2009, pp. 2371–2374.
- [5] J. M. Girault and Z. Zhao, "Synchronous detector as a new paradigm for automatic microembolus detection," *International Journal of Biomedical Engineering and Technology*, vol. 14, no. 1, pp. 60–70, 2014. [Online]. Available: <https://tel.archives-ouvertes.fr/UNIV-TOURS/hal-01077276v1>
- [6] C. C. of the Ninth International Cerebral Hemodynamic Symposium, "Basic identification criteria of doppler microembolic signals," *Stroke*, vol. 26, no. 6, p. 1123, 1995. [Online]. Available: <http://stroke.ahajournals.org/content/26/6/1123.short>
- [7] F. Lin, C. Saglio, M. Almar, B. Guibert, and P. Delachartre, "Microembolic signal characterization based on long time doppler time-frequency image processing and statistics," in *Signal Processing (ICSP), 2014 12th International Conference on*, Oct 2014, pp. 1046–1051.
- [8] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, no. 285-296, pp. 23–27, 1975.
- [9] T. Chan and L. Vese, "Active contours without edges," *Image Processing, IEEE Transactions on*, vol. 10, no. 2, pp. 266–277, Feb 2001.
- [10] F. Millioz and N. Martin, "Estimation of a white Gaussian noise in the short time Fourier transform based on the spectral kurtosis of the minimal statistics: Application to underwater noise," in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, 2010, pp. 5638–5641. [Online]. Available: <http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5495260>
- [11] —, "Circularity of the stft and spectral kurtosis for time-frequency segmentation in Gaussian environment," *IEEE Trans. Signal Process.*, vol. 59, no. 2, pp. 515–524, 2011. [Online]. Available: <http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5590308>