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# Contribution to Structural Intensity Tool : Application to the Cancellation of ECG Interference in Diaphragmatic EMG

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*Abstract*—**This paper is concerned with the problem of localizing the typical features of a signal when it is observed with noise in order to align a set of curves. Structural intensity (SI) is a recent tool that computes the "density" of the location of the modulus maxima of a wavelet representation along various scales in order to identify singularities of an unknown signal. As a contribution to this novel approach we establish a modified SI using the Berkner transform which allows maxima linkage to insure accurate localization of singularities. An application to cancellation of ECG interference in diaphragmatic EMG is also proposed.**

**Keywords : continuous wavelet transform, diaphragmatic EMG, ECG cancellation, landmark-based registration , wavelet maxima linkage.**

## I. INTRODUCTION

In this paper, we propose to use the continuous wavelet transform of a signal to determine its structural points called landmarks, and we mainly focus on the problem of the location of the singularities. Looking at a signal at different levels of scale decomposition for characterizing its local structure has been widely and successfully used in the scale-space literature [1]. In particular, wavelet transforms have successfully demonstrated their good localization properties of the structure of a signal [2]. In the context of signal processing, the propagation across scales of the modulus maxima of a scale-space transform is a powerful tool to analyze the typical features of a signal [1], [3]. The characterization of the features of a noisy signal is of fundamental importance for landmark-based registration. A new tool, the structural intensity (SI), was introduced recently to represent the locations of the typical features of a curve via a probability density function [4], [5]. This method provided a new technique to put into correspondence the landmarks of two signals. The main modes of the SI correspond to the significant landmarks of the unknown signal. A drawback of this method is time delocalization of singularities when the considered scales increase.

Our aim is to modify SI in order to insure accurate localization and maintain robust detection of singularities in a noisy signal. In this paper, we first modify SI using Berkner transform (BT) which offers maxima linkage facility [6]. Secondly, to illustrate the modified SI tool utilization, we apply the method to cancel electrocardiographic (ECG) interference in the electromyogram of the diaphragm (EMGdi) using a method based on an "event–synchronous canceller" (ESC) proposed by [7]. We show how we built an artificial ECG template segment by synchronizing QRS waveforms from landmarks detected on modified SI.

## II. METHODS

### A. Continuous wavelet transform

The wavelet transform (WT) is a decomposition of the signal as a combination of a set of basis functions, obtained by means of dilatation ($s$) and translation ($x$) of a single prototype wavelet $\psi(t)$. Thus, the WT of a signal $f(t)$ is defined as :

$$W_s(f)(x)=\frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty}f(t)\psi^*\left(\frac{t-x}{s}\right)dt \quad (1)$$

The greater the scale factor $s$ is, the wider is the basis function and, consequently, the corresponding coefficient gives information about lower frequency components of the signal, and vice versa. In this way, the temporal resolution is higher at high frequencies than at low frequencies. The term wavelet maxima (or modulus maxima) is used to describe any point $(m_0, s_0)$ in the time-scale plane such that $z \mapsto |W_{s_0}(f)(z)|$ is locally maximum at $z = m_0$. This local maximum should be a strict local maximum in either the right or the left neighbourhood of $m_0$. These maxima define curves in the time-scale plane which are called maxima lines.

### B. Structural intensity

The SI method [4], [5] uses the maxima of $W_s(f)(x)$ at various scale to compute a "density" whose local maxima will be located at the singularities of *f*. For $x \in \Re$, the

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structural intensity of the wavelet maxima $G_m(x)$ is defined as :

$$G_m(x) = \frac{1}{M}\sum_{i=1}^{q}\int_{s_{\min}}^{s_{\max}} \frac{h_i(s)}{s}\theta\left(\frac{x - m_i(s)}{s}\right)ds$$

$$\text{with } h_i(s) = \frac{|W_s(f)(m_i(s))|}{s^{r+1/2}} \qquad (2)$$

where $[s_{\min};s_{\max}]$ is the considered support of the lines $m_i(.)$ in the time-scale plane, $q$ is the number of maxima lines, $\theta$ is chosen as a Gaussian when $\psi$ is a Gaussian derivative, $r$ the vanishing moment of the wavelet, and $M$ is a normalization constant to consider $G_m(x)$ as a probability density. If $\theta$ has a compact support equal to $[-I, I]$, the assumptions (2) mean that the wavelet maxima lines converging to $x_i$ must be strictly included in the cone of influence of $x_i$ defined as the set of points $(x, s)$ such that $|x - x_i| \leq I_s$. So, the maximum of singularity $x_i$ is delocalized in large scales. If $m_i(s)$ converges to a singularity of order $0 \leq \alpha < r$ then, at fine scales, $h_i(s)$ behaves like $s^{\alpha - r}$.

Equation (2) shows that, in practice, the landmarks of a function can be obtained by the locations of the local maxima (or modes) of $G_m(x)$. Fig. 1 illustrates the detection of the landmarks of a signal with singularities via the structural intensity of its wavelet maxima lines. One can see that the amplitude of a mode of $G_m(x)$ varies with the number and the length of the support of the lines $m(s)$ that converge to it . We must remind that the amplitude of a mode of $G_m(x)$ also depends on $h_i(s)$ values.

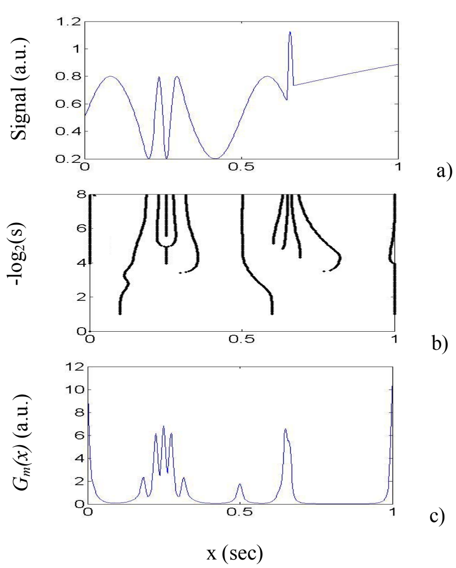


Fig. 1. (a) Signal with singularities. (b) Time-scale representation of maxima lines. (c) Original SI calculated with (2) from $s_{\min} = 2$ to $s_{\max} = 128$ (2 Hz - 150 Hz).

*C. Berkner transform*

The study of extrema of signal decomposition over Gaussian or derivatives of Gaussian functions is a good means to solve the problem of time delocalization of singularities. Indeed, extrema that arise from the convolution of the signal with Gaussian functions or derivatives of Gaussian functions are known to form connected curves in the time-scale space [8], which link any singularity at a given scale to its origin at the finest scale. However, the practical construction of the maxima lines associated with these wavelet decompositions require ad-hoc procedures. We, therefore, use BT which is an approximation of the Gaussian derivative wavelet transform based on a hierarchical scheme similar to the popular fast discrete wavelet transform [6], [9]. It is easy to compute and a simple relation [9] enables us to follow the maxima lines in the time-scale plane. More precisely, BT is achieved through the discrete convolution of a signal $f$ with the following approximation of the first derivate of a Gaussian [6] :

$$\rho_N(k) = 2^{-N}\left(1 - \frac{k}{N-k+1}\right)c_k^N$$

$$\text{with } c_k^N = \frac{N}{k!(N-k)!} \qquad (3)$$

where $k$ is the sampled time and $N$ the scale of the wavelet.
From (3) it is easy to demonstrate that :

$$\rho_N(k) = \frac{1}{2}\left(\rho_{N-1}(k) + \rho_{N-1}(k-1)\right) \qquad (4)$$

Owing to this, it is possible to follow a maximum from scale N to scale N+1. In [9] a modified Berkner expansion is proposed :

$$\bar{c}_N(k) = \sum_{j=0}^{\infty}\bar{\rho}_N(k)f(k+j)$$

$$\text{with } \bar{\rho}_N(k) = \bar{\rho}_N\left(k + \left\lfloor\frac{N+1}{2}\right\rfloor\right) \qquad (5)$$

so the recurrence relation (2) was also modified and led to :

$$\bar{c}_N(k) = \frac{1}{2}\left(\bar{c}_{N-1}(k) + \bar{c}_{N-1}(k-1)\right) \text{; if N+1 was even}$$

$$\bar{c}_N(k) = \frac{1}{2}\left(\bar{c}_{N-1}(k) + \bar{c}_{N-1}(k+1)\right) \text{; if N+1 was odd} \qquad (6)$$

*D. Modified SI*

*First modification : Comparison with original formula*

To avoid delocalization due to temporal resolution at large scales, we use BT which allows to link maxima, and we rewrite (2) as :

$$G_m^*(x) = \frac{1}{M}\sum_{i=1}^{q}\sum_{N=N_{\min}}^{N_{\max}}\frac{h_i(N)}{N}\theta\left(\frac{x - x_0(m_i(N))}{N}\right)$$

$$\text{with } h_i(N) = \frac{\left|\bar{c}_N(m_i(N))\right|}{N^{r+1/2}} \qquad (7)$$

where $x_0$ is the position of $m_i(N)$ at the finest scale.

In Fig. 2 and Fig. 3, we can compare modes of original SI and modified SI. $G_m(x)$ and $G_m^*(x)$ were calculated in the same range of frequencies (2 Hz - 20 Hz), so local maxima of $G_m(x)$ and $G_m^*(x)$ represent landmarks associated with this range of frequencies. We can observe a shift of SI modes in comparison with the landmarks (vertical dashed lines) in Fig. 2. This shift is corrected in Fig. 3 with modified SI.

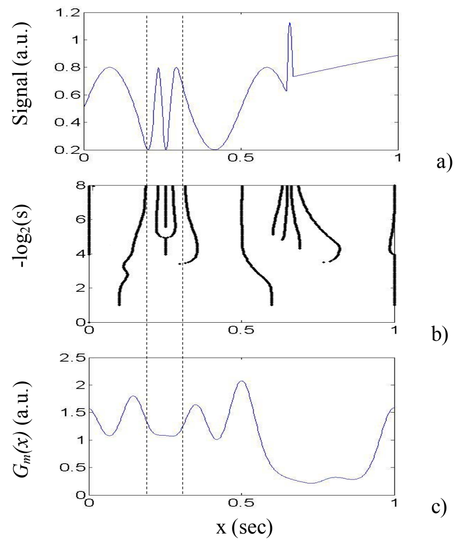


Fig. 2. (a) Signal with singularities. (b) Time-scale representation of maxima lines. (c) Original SI calculated with (2) from $s_{\min} = 2$ to $s_{\max} = 16$ (2 Hz - 20 Hz).

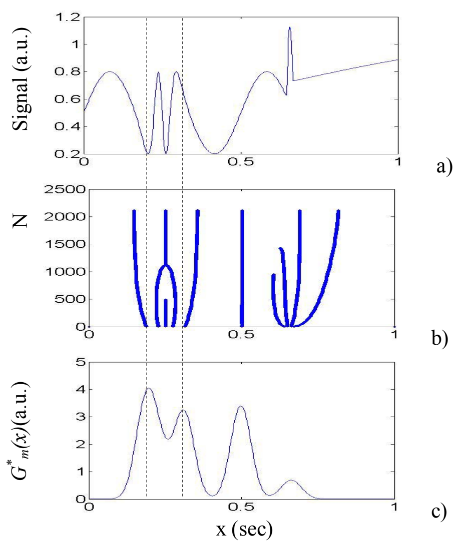


Fig. 3. (a) Signal with singularities. (b) Time-scale representation of maxima lines. (c) Modified SI calculated with (6) between $N_{\min} = 1000$ and $N_{\max} = 2000$ (2 Hz – 20 Hz).

*Second modification : Event detection on SI*

In the calculation of SI, we can choose the range of scales [ $N_{\min}, N_{\max}$ ] allowing the creation of modes which are specific to events that we wish to detect. The robustness of the detection can be then ensured by a choice of pertinent scales and temporal information related to the duration of the event. In (2), the kernel $\theta$ takes into account the cone of influence because its size varies as a function of scales. As the problem of delocalization is solved with maxima linkage, the kernel can be chosen with a fixed pertinent duration that will depend on the parameter $T$ as follows :

$$G_m^{**}(x) = \frac{1}{M}\sum_{i=1}^{q}\sum_{N=N_{\min}}^{N_{\max}} h_i(N)\theta\left(\frac{x - x_0(m_i(N))}{T}\right) \qquad (8)$$

Fig. 4 shows the influence of the duration of the kernel.

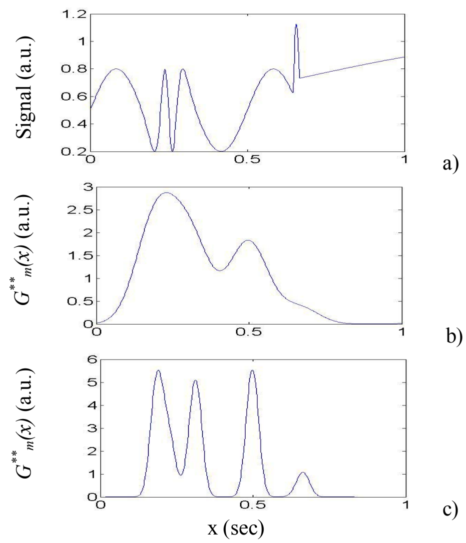


Fig. 4. (a) Signal with singularities. (b) Modified SI with $T$=1000. (c) Modified SI with $T$=100.

## III. APPLICATION TO THE CANCELLATION OF ECG INTERFERENCE IN EMGDI

### *A. The "Event-Synchronous interference Canceller" (ESC) concept [7]*

An event-synchronous interference canceller (ESC) has already been applied to the removal of ECG interference from EMGdi signals. Fig. 5 shows the concept of the ESC. The basic idea of ESC as described in detail by [7] assumes that the "cleaned" EMGdi signal is obtained by direct subtraction of the reference input from the primary input. A very important aspect of this approach is the correct alignment of the "artificial" template ECG segment with the actual ECG interference within the EMGdi signal. The generation of an artificial reference signal requires QRS synchronous segmentation of the ECG waveform. The system needs a reference input which is the ECG itself.

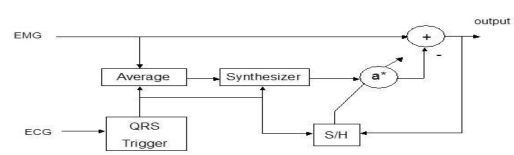


Fig. 5. Principle of the ESC from [7].

### *B. The "SI Event-Synchronous interference Canceller"*

Our aim is to create a tool to cancel ECG events within the EMGdi signal without recording a separate reference ECG. In order to insure accurate but also robust detection, we used the modified SI and the principle described above in Fig. 5. Fig. 6 shows these modifications.

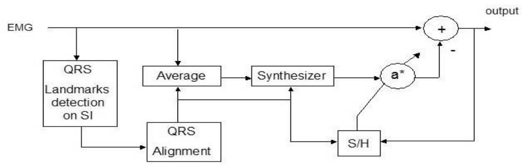


Fig. 6. Modified principle of the ESC with SI.

For this, EMGdi was sampled at a frequency of 2 kHz and filtered between 20 Hz and 800 Hz. The EMGdi signal was recorded with two surface electrodes placed in the 7th and 8th intercostal spaces.

*First step : detection of QRS waveform in EMGdi*

We start by detecting modes specific to ECG. So in (8), parameters are chosen to correspond to ECG features :

- $N_{\min} = 2000$, $N_{\max} = 2700$ (10 Hz - 15 Hz);
- $\theta$ is a rectangle window with duration of 180 ms.

An example is shown in Fig. 7.

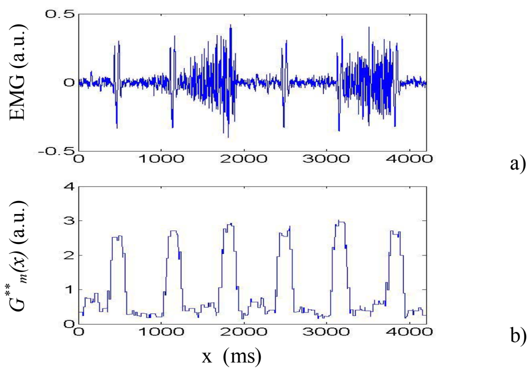


Fig. 7. (a) EMGdi with ECG interference. (b) Modified SI with detection of QRS waveforms.

*Second step : synchronization of QRS waveform in EMGdi*

To generate the artificial reference signal based on a basic template QRS waveform, we need to synchronize ECG segments (400 ms). This matching can be done by aligning individual locations of landmarks corresponding to SI above a given threshold, and to lines with support above $N_{\min}$, from one QRS curve to another. The alignment of the QRS waveforms in Fig. 7 is shown in Fig. 8.

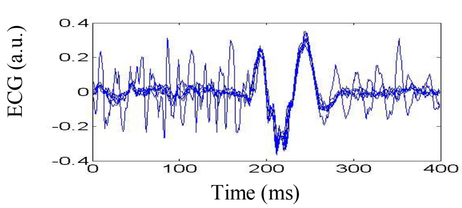


Fig. 8. Alignment of QRS waveforms.

*C. Results*

The "cleaned" EMGdi is now obtained by direct subtraction of the reference input from the primary input. Fig. 9 shows results obtained with our method and those of the "ESC" method. No significant difference between them can be found by visual inspection.

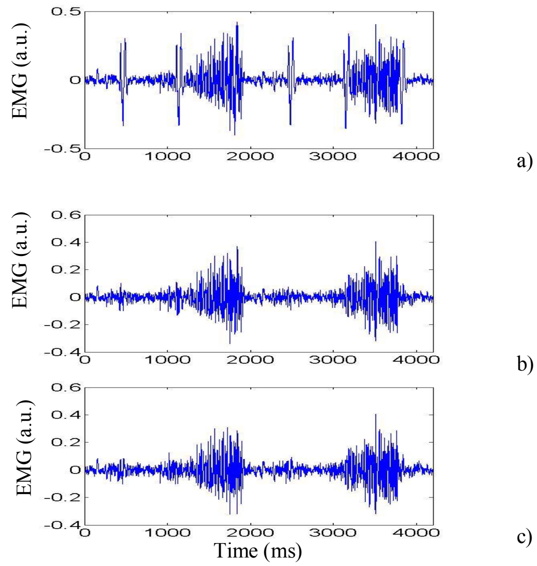


Fig. 9. (a) EMGdi with ECG interference. (b) "Cleaned" EMGdi with modified SI. (c) "Cleaned" EMGdi with method [7].

## IV. CONCLUSION

In conclusion, we show combining modification of SI with BT allows us to accurately localize singularities of a noisy signal. This tool was successfully applied for the removal of ECG interference from EMGdi in human subjects.

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