TRANSIENT SIGNAL DETECTION USING OVERCOMPLETE WAVELET TRANSFORM AND HIGH-ORDER STATISTICS

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ABSTRACT

In this paper we consider the problem of the transient signal detection, followed by a virtual characterization stage. There are two main difficulties which appear in this field. The first one is due to the noise which acts in a real environment. Secondly, when we are interested about signal characterization, it is important to provide a more complete information about its time-frequency behavior.

Consequently, we propose an adaptive time-frequency method based on the over-complete wavelet transform concept, in which case an irregular sampling procedure will be involved. This procedure uses a method based on the fourth order moment, applied for each sub-band, in order to establish the optimal weight for each sample. The results obtained for real data prove the capability of the proposed approach to accurately detect a transient signal, comparatively with some classical methods (spectrogram or standard wavelet transform, for example).

1. INTRODUCTION

The problem of detecting transient signal of unknown waveforms has been widely studied in recent years due to the numerous applications associated with it. Some applications field are : medical signal processing, non-destructive defectoscopy, underwater signal processing, etc. In these applications we are interested in both the detection of the useful part of signal and its characterization. In this case, there are two major problems that can be solved. Firstly, the processing system must to be able to accurately detect the transient parts of the signal. One of the most performant detection methods is based on the joint use of the wavelet techniques and the high order statistical measurement [1]. For the second problem - *signal characterization* - it is necessary to use a method which could be able to extract the useful information about the processed data, knowing that the real environments are generally highly non-stationary. In this context, the use of time-frequency methods [2] can be a potential solution. This class of methods must be able to provide a suggestive information about the signal structure. Currently, this information is provided on the time-frequency image form and, the quality of this image strongly influences the performances of the following processing stages.

In this work we propose a method based on the Over Complete Wavelet Transform (OCWT) which leads to signal processing on interest frequency sub-bands. In each of them, an irregular sampling procedure will be used, in order to optimally detect the useful signal features. The results will be done in a time-frequency image form corresponding to the frequency content variation over time.

The organization of this paper is as follows. In section 2 we briefly present the OCWT concept. In section 3 we propose a new irregular sampling procedure, based on a *split and merge* algorithm. As we will see, the *kurtosis* will be used as a cost function. In section 4 we will study the performances of our approach from a theoretical point of view (with help of the *receiver operating characteristic - ROC*) and using the real underwater mammals signals . Beside, we will compare the obtained results with the ones obtained by the classical method (Spectrogram, Discrete Wavelet Transform). Section 5 - "Conclusion" - highlights the significance of the results and the realistic perspectives.

2. OVERCOMPLETE WAVELET TRANSFORM

In many applications, due to their remarkable procedures, the discrete wavelet transform (DWT) has been extensively used [3].

From a mathematical point of view, the DWT is generated by sampling, in the time-scale plane, of a corresponding continuous wavelet transform (relation 1).

$$(W_g f)(t,s) \overset{\Delta}{=} \langle f, \tau_t D_s g \rangle = |s|^{1/2} \int f(u) g^*(s(t-u)) du \quad (1)$$

where g is the analyzing wavelet, f is a given signal, τ_t is the translation operator ($((\tau_t f)(u) = f(u-t))$) and D_s is the scale operator ($(D_s f)(u) = \frac{1}{s} f\left(\frac{u}{s}\right)$). Despite the fact that there is an infinity of possible discretization of the CWT, the term *discrete wavelet transform (DWT)* is commonly used to mean the one associated with the dyadic sampling lattice.

$$\Gamma_D \overset{\Delta}{=} \left\{ \left(2^{-n} m, 2^n \right) \right\}_{m,n \in Z} \qquad (2)$$

for certain analyzing wavelets that give rise to wavelet orthonormal basis.

In practice, it was observed, that the use of orthonormal representation is not necessariy well suited for a given signal processing problem [4]. For example, by regular sampling, used to compute the MRA, we can loose the signal characteristics, represented by its maxima.

Consequently, the orthonormal representation drawbacks are due to the dyadic grid. In order to eliminate them, the key point is the use of a non-dyadic sampling structure, which is the case of the OCWT [5]. This method is composed by two stages :

I. Firstly, we decompose the signal with the linear filter bank structure. The impulse responses of the filter bank are determined by the analyzing wavelet g and the scale samples s_m. The filtering stage result is presented in the next equation.

$$W_g f\left(t, s_m\right) = \left(f * D_{s_m} g^* \right)(t) \qquad (3)$$

Here s is a scaling index which controls the filter bandwidth and the central frequency of each filter. In addition, we can control the overlapping between the filter transfer functions (figure 1.b). For $s=2$, we obtain the filter bank structure used for the DWT computation; a filter bank example is shown in 1.a., using the Morlet wavelet as the analyzing function, which has the following analytical expression :

$$g_{Morlet}(t) = \frac{1}{\sqrt{p g_b}} \cdot e^{j 2 p g_c t - (t^2 / g_b)} \qquad (4)$$

where g_b and g_c are the bandwidth and the frequency center of the g Fourier transform.

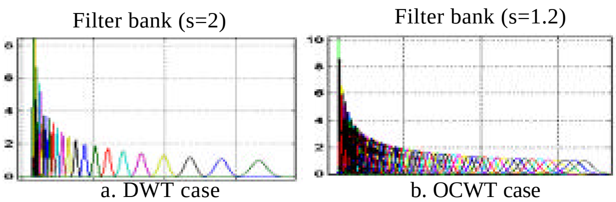

Figure 1. Comparison between filter banks at different scales

II. In the second stage we will sample the signal issue at the filter bank output. We take into account the samples at discrete times given by $\{t_{m,n}\}$.

Mathematically, OCWT may be interpreted as the CWT sampled version of the signal by a non-dyadic structure. Usually, we use the semi-logarithmic regular sampling, given by the next definition [4].

$$\Gamma\left(\Delta, a_0\right) \overset{\Delta}{=} \{n\Delta\} \times \left\{ a_0^m \right\}, 2 > a_0 > 1, \Delta > 0 \qquad (5)$$

Consequently, the a_0 parameter controls the filter overlapping, and, implicitly, the redundancy degree. If a_0 is 2, the redundancy will be null : the wavelet basis will generate an orthonormal reconstruction error null, but the extraction of the signal characteristics is not guaranteed. If a_0<2, the wavelet function set will be a frame : the reconstruction is not perfect but *we can adapt our distribution to the signal time-frequency structure.*

3. IRREGULAR SAMPLING PROCEDURE

Generally speaking, there are some advantages to adopt an irregular sampling strategy in a representation. Many of these advantages are inherited from the ability of an irregular sampling to be sensitive to signal time-frequency behaviors [4]. The theoretical frame of the irregular sampling strategies is presented in [5] and some applications (for noise suppression, digital communication, compression, etc.) are presented in [4]. In this section we introduce a new irregular sampling technique, well adapted for transient signal detection, in a noisy environment. This technique will be applied to the corresponding waveform, provided by OCWT for each frequency channel.

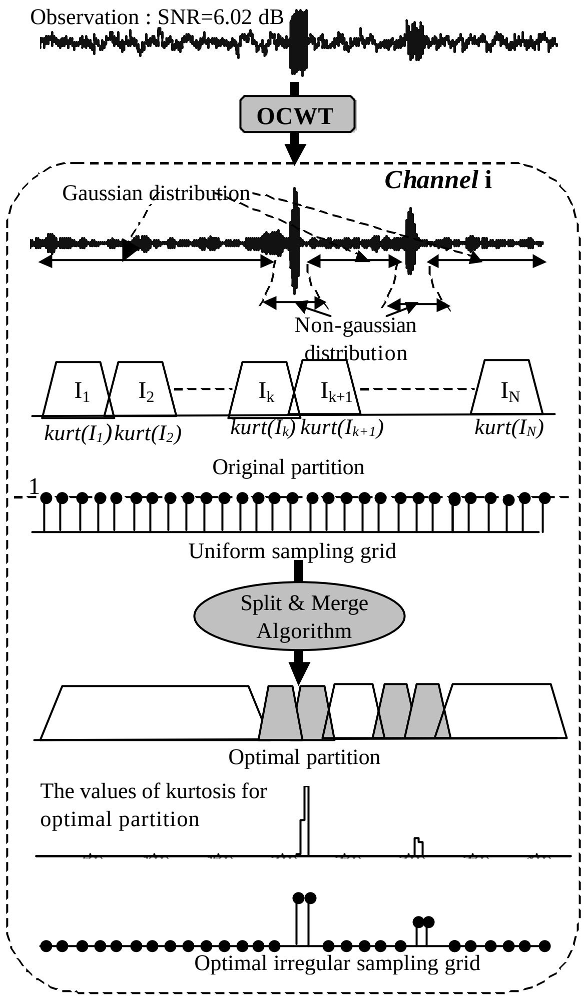

Figure 2. The Irregular sampling procedure for channel *i*

It is well known [6] that the non-gaussian wavelet coefficients provide a large value of a fourth order statistic moment (*kurtosis*). On the other hand, the noise coefficients, which currently have a gaussian probability density function, provide a small value of the *kurtosis*. The kurtosis allows us to discriminate between the useful (transitory) and useless (noise) parts of the signal. This principle will be applied to detect an optimal sampling grid for each signal's representation, issued from OCWT.

In the above figure we present the principle of the irregular sampling procedure. The waveform issued from *i*-channel of the OCWT filter bank is uniformly partitioned in equal length intervals. For each of them the value of kurtosis is estimated, using the following relation [6]:

$$kurt(I_k) = N\left(\sum_{i=1}^{N} x_i^4\right) \Big/ \left(\sum_{i=1}^{N} x_i^2\right)^2 ; \{x_i\} \in I_k \quad (6)$$

Using these values, we apply an iterative split & merge algorithm in order to establish the optimal partition.

For each two adjacent intervals I_k et I_{k+1}, we test the following condition :

$$H_0: \text{ if } kurt(I_j) \le m_s \ \& \ kurt(I_{j+1}) \le m_s \Rightarrow I'_j = I_j \cup I_{j+1}$$
$$\Rightarrow \text{kurt}(I'_j) = \max[kurt(I_j), kurt(I_{j+1})]$$
$$H_1: \text{ if } kurt(I_j) > m_s \text{ or } kurt(I_{j+1}) > m_s \Rightarrow \text{the intervals will be conserved}$$

The H_0 hypothesis states that there is no useful part in the considered intervals, so, these ones will be *merged* (fusion). Alternatively, The H_1 hypothesis states that one or both intervals are subject to the useful parts of signals and will be *conserved*. The algorithm runs until no fusion is possible.

The involved threshold μ_s is computed for each channel using the following formula [1,6] :

$$\mu_s = \frac{1}{\sqrt{1-a}} \sqrt{a_0^s \frac{24}{N}} \quad (7)$$

where a - is a confidence degree [6], a_0 is the overlapped degree (see the previous section), N is a sequence length and s is the channel index (*s=1:Number_of_channels*).

Finally, we obtain an optimal partition (figure 4) and the values of the kurtosis for the optimal partition. The obtained curve weights the samples of the supposed waveform, ensuring an irregular sampling of this one : the samples associated to transient parts of signal will be "highlighted", whereas the ones associated to noise will be almost precluded. This effect is illustrated in the figure 3. We consider two chirps atoms (both on 128 samples), mixed with real oceanic noise (SNR=6.02 dB). After the OCWT (the number of the channels is about 128) we apply the method to the extracted waveform from each channel. The values of kurtosis for the optimal partition provide an optimal sampling grid which improves the representation quality. Repeating the same algorithm for all OCWT channels, we obtain a two-dimensional irregular sampling grid which leads to an optimal time-frequency regions-of interest (ROIs) detection (figure 3). On the other hand, by unifying the kurtosis curves of the all sub-bands and for all temporal position, we obtain *the detection curve* in both time and frequency domains, which provide an information about temporal localization of the transient parts of the signals. For the considered test signal, the detection curves are shown in the figure 3.

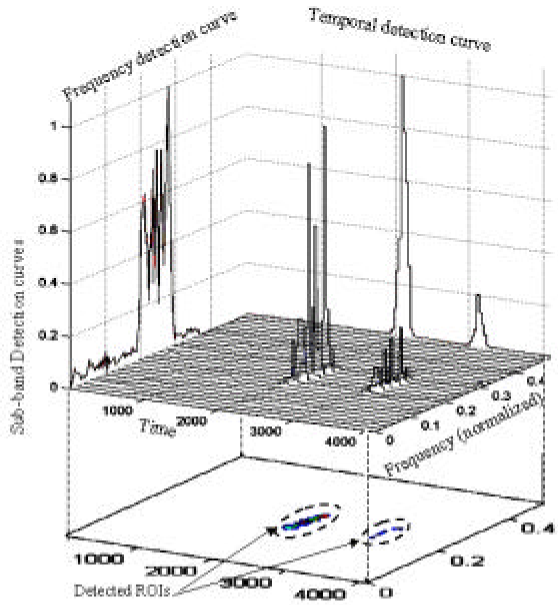

Figure 3. Detection of the time-frequency ROIs, using the OCWT and the irregular sampling procedure

4. RESULTS

Here, we comparatively present the detection results obtained by our method (OCWT-IS - irregular sampling) and two classical ones : spectrogram [2] and discrete wavelet transform [3].

First, as a performance measure the receiver operating characteristics (ROC) have been measured (figure 4). Recall that the ROC is a collection of curves describing the probability of detection as a function of the probability of false alarm for a set of different signal to noise ratio (SNR) [6].

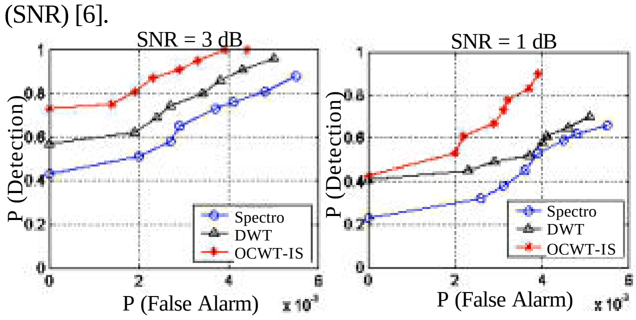

Figure 4. Experimental ROCs for Detection schemes based on the spectrogram, DWT and OCWT-IS

Clearly, this figure indicates that the OCWT based method outperforms good detection performances in every case. Firstly, we obtain the satisfactory value for the detection probability, even for a SNR close to 0 dB. Secondly, the false alarm level is lower than the values generated by the first two methods. Both of these facts demonstrate the superiority of the OCWT-IS based detector.

The detection method based on the OCWT-IS procedure not only provides nice detection performances (see figure 4), but also leads to a good resolution time-frequency image. This allows us the opportunity to accurately extract the useful information carried by the detected transient signal. To prove that, we have tested our approach with real data corresponding to the signal emitted by a long-finned pilot whale (*Globicephala melas*). The sampling frequency is 44.1 kHz and we have taken into account an observation of 5.92 seconds. The test signal is presented in the figure 5.a.

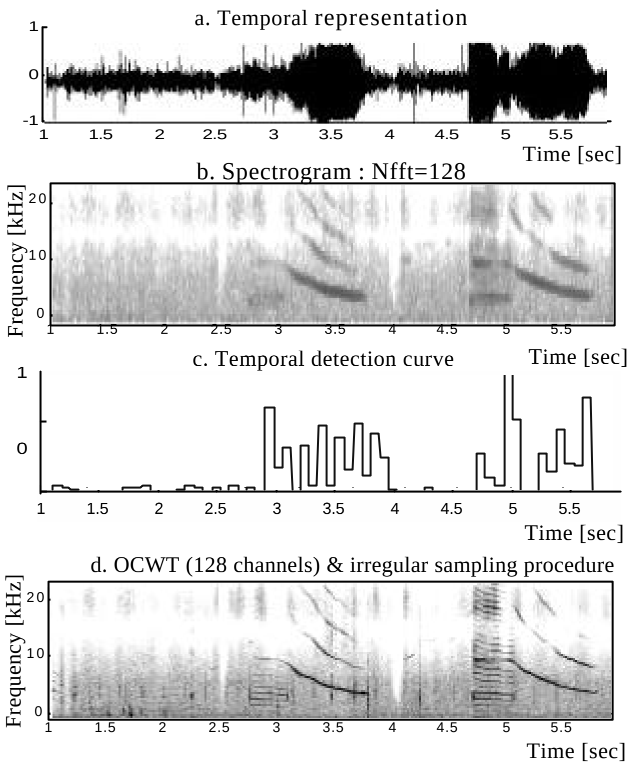

Figure 5. Comparative results for real analysis data

In the figure 5.b., the spectrogram of this signal is presented. In this case, there is a trade off between time and frequency resolutions which affect the signal feature representation.

Using our method, we obtain the corresponding ROIs where the transient parts of signal occur (figure 5.c). Furthermore, we observe that the time-frequency signal features are energetically *stronger* than the noise components. Therefore, the Generalized Matching Pursuit-based time-frequency representation (GTFR) proposed in [7], will correctly perform, as it is depicted in the next figure.

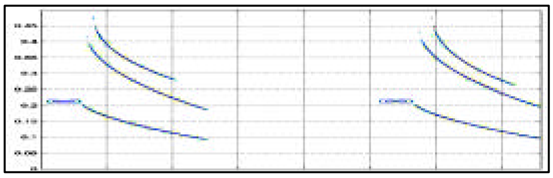

Figure 6. GTFR of the real signal

The GTFR, applied in each ROIs previously detected, ensures an analytical representation of the instantaneous frequency law [8]. On the other hand, the signal partition in the ROIs, provided by OCWT-IS, allows to a considerable generalized dictionary *reduction* ([8]), bringing the GTFR applicable for the real signals. More specifically, the idea is to compute a particular generalized dictionary for each ROI, reducing also the number of the component that will be searched via the algorithm described in [7].

5. CONCLUSIONS

As it was proved by the experimental results, the ROIs detected by the proposed method provide a complete and satisfactory information about time-frequency behaviors of the considered signals. Consequently, due to its good readability, it may be successfully used for a further feature extraction algorithm.

In further works, we intend to use this algorithm as a feature extraction method in the context of underwater transient signal classification.

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