TIME-FREQUENCY DETECTION USING GABOR FILTER BANK AND VITERBI BASED GROUPING ALGORITHM

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ABSTRACT

Problem of signal detection, followed by a characterization stage is considered in this paper. The main difficulties arising in the detection stage are caused by noise, which acts in a real environment, and by multiple time-frequency (TF) structures of the signal. In this paper a detection method based on the adaptive grouping of the TF information provided by a Gabor filter bank is proposed. A Viterbi-type algorithm is used as a tool for grouping of TF components. The results obtained for real data prove the capability of the proposed approach for accurately detect and characterize signals with a complex TF behavior.

1. INTRODUCTION

The problem of detecting signal of unknown waveforms has been widely studied in recent years due to the numerous applications associated with it. Some application fields are: medical signal processing, non-destructive machinery diagnostic, 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 should 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 higher 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 the TF methods [2] can be a potential solution. This class of methods must be able to provide suggestive information about the signal structure. Currently, this information is extracted from the TF image form. The quality of the TF image strongly influences the performances of the following processing stages.

In this work we propose a method based on the Gabor filter bank processing which leads to signal processing on selected frequency sub-bands. Furthermore, the information provided by the filter bank is grouped via Viterbi algorithm. The purpose of this operation is to ensure the conservation of the TF behavior of the detected parts of the signal. According to this task, a new objective function is defined.

The results provided for real data would prove the performances of the proposed approach to work in an operational context.

The organization of this paper is as follows. In section 2, we briefly present the Gabor filter bank structure and its application in the detection field. In section 3 we present the Viterbi algorithm as a tool for grouping the TF information provided by the filter bank. The detection method, based on the combination between Gabor filter bank and Viterbi algorithm, is described in the section 4. Some results, provided for simulated signals, are presented in section 5. Section 6 highlights the significance of the results and the realistic perspectives.

2. GABOR FILTER BANK - DETECTION PERSPECTIVE

A signal may contain numerous TF components with complex structure. An efficient detection stage must take into account this frequency diversity. Moreover, the detection step is usually done to avoid heavy processing on complex signals with high sampling rate. To achieve this purpose, we propose to use a simple filter bank and a grouping strategy to separate the different components by detecting the regions of interests (RoI). From these RoIs, we could obtain denoised signals at lower sample rate, on which more complex processing can be done.

To cover the whole frequency band of the signal, we use N_f filters with equidistant central frequencies f_k. Gabor atoms were chosen for the filter bank decomposition. Namely, the Gabor function exhibits optimal joint TF support in the TF plane leading to the optimal separation capability between close signal components. The non-causal impulse response of the Gabor atom is given by $h_k(t) = Ae^{-t^2/2\sigma^2} e^{2i\pi f_k t} = h(t)e^{2i\pi f_k t}$ where σ and f_k are respectively the variance parameter of the Gaussian windows $h(t)$ and the central frequency of the atom. The Gabor atom time and frequency supports are defined by (1).

$$\sigma_t^2 = \frac{\int_{-\infty}^{\infty} t^2 |h(t)|^2 \, dt}{\int_{-\infty}^{\infty} |h(t)|^2 \, dt} = \frac{\sigma^2}{2} \quad \sigma_f^2 = \frac{\int_{-\infty}^{\infty} f^2 |H(f)|^2 \, df}{\int_{-\infty}^{\infty} |H(f)|^2 \, df} = \frac{1}{8\pi^2\sigma^2} \quad (1)$$

The product of time and frequency supports achieves minimum given by the uncertainty principle $\sigma_t\sigma_f = 1/4\pi$. The pass band of each filter is defined by $BP = 1/2\sqrt{2}\,\pi\sigma$ and must be chosen, accordingly to N_f, to cover the necessary frequency band. A measure of the frequency coverage can be given by $G(\omega) = \sum_{p=1}^{N_f} |H_k(\omega)|^2$, as defined in [7], where $H_k(\omega)$ is the Fourier transform of $h_k(t)$. A plot of this function is depicted in figure 1.

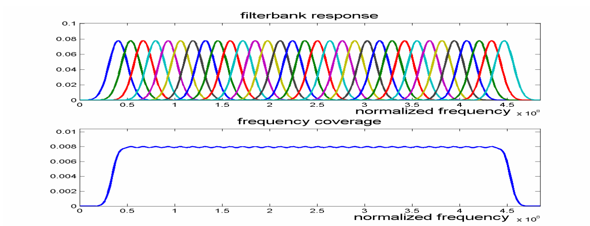

Figure 1. Filter bank and frequency coverage

Different kind of processing can be carried out on filters outputs for detection. One of the easiest is to perform a block processing using statistics in order to detect the bands containing energy. The neighbouring bands over a threshold could then be grouped to form more accurate filters in the time domain. Half of the detection is then done and the remaining filters output with less energy can be neglected.

With this energetic group of filters, the time support can also be estimated using higher-order statistics, with kurtosis for example [1]. By selecting the estimated time support of the grouped filter outputs, the RoIs selection is done and the component extracted.

This grouping strategy involves several drawbacks. Firstly, we cannot separate close components whose instantaneous frequency (IF) is varying in time. Secondly, the detected TF regions of interest, using this kind of algorithm, will be rectangular boxes. It is then easy to see that a component can hide another one both in time and frequency.

To improve the detector and solve this kind of problem, an adaptative implementation based on the Viterbi-like algorithm could be done. At each sample, the output of the filters will be processed to adapt the grouping of the filters.

3. VITERBI ALGORITHM

The Viterbi algorithm is proposed for the decoding of convolutional codes. It has itself very interesting background since Viterbi proposed it only for educational purposes. Other authors later proved its significant practical importance. The Viterbi algorithm could be assumed as dynamical programming search problem. In wider context it can be considered as a tool for detection of hidden states in signals. Extensions of the Viterbi algorithm are used in numerous fields, like for example in image processing for edge following. Its main advantage over other related methods is simple recursive realization that reduces search space in the case of very complicated and nonlinear problems. Recently, the Viterbi algorithm was applied in the TF analysis as a tool for the IF estimation.

The Viterbi algorithm based IF estimator is defined as a path through the TF plane which minimizes the sum of path penalty functions:

$$\hat{\omega}(t) = \arg\min_{k(t)\in\mathbf{K}} \left[\sum_{m=1}^{N-1} \gamma(k(t), k(t+\Delta t)) + \sum_{m=1}^{N} \lambda(TF(t,k(t))) \right] \quad (2)$$

where it is assumed that the IF function could pass only through discrete set of frequency bins $\mathbf{K}$, Δt is sampling rate and N is number of considered instants, the $TF(t,\omega)$ is considered TF representation. The path penalty functions are selected to meet the following criterions: IF function passes trough the high magnitude points in the TF plane (function $\lambda()$); IF is relatively slow varying function (function $\gamma()$). Particular selection of path penalty functions and algorithm realization is discussed in [3].

The Viterbi algorithm can be extended as a general tool for grouping together parts of the TF plane belonging to the same signal component. Some adaptations must be done to deal with the multicomponent case and to tackle the problem of detecting the beginning and the end of each component. Details on the path penalty function modification for the considered application are presented in the following section.

4. DETECTOR BASED ON VITERBI GROUPING OF THE FILTER BANK INFORMATION

The algorithm described in [3] is based on the pseudo Wigner-Ville representation and deals with the monocomponent case. It supposes that there is an IF to estimate from the beginning to the end of the signal. For a multicomponent detection purpose, we must get rid of these assumptions and adapt this algorithm to the Gabor filter bank. As illustrated in figure 2, the aim is to identify the group of filters containing a TF evolving signal. In [3], where only one component has to be estimated, all the points with the highest magnitude values of the TF representation, at one instant were candidate, for the IF estimate. To deal with the multicomponent case, another way is chosen to select the candidates. Namely, at instant i, we will estimate all the maxima, over a threshold, of the filter output modules as described in the figure 2. This set will be denoted as C_i. The bandwidths, related to the frequency spreading of the components, will be associated to these maxima. The aim of the detection algorithm is then to associate all the maxima belonging to a component. Knowing the bandwidth associated with each maximum, i.e. the number of filters concerned for a component at one instant, this component will be well localized in the TF plane. The associated RoI is then well determined and the signal can be extracted.

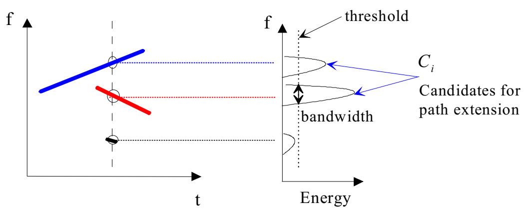

Figure 2. Maxima detection

Threshold estimation

Depending on the signal composition at each instant, the threshold must be adapted. The energy $PW_n(i)$ is computed recursively over a window, of length N_w+1, at the output of the filter n, giving an average energy repartition of the signal in the frequency bands at one instant (3).

$$PW_n(i) = 1/(Nw+1)\sum_{j=i-Nw/2}^{i+Nw/2} \left|TF\left(t_j, \omega_n\right)\right|^2 \qquad (3)$$

We consider this energy repartition as a signal $s_i(n)=PW_n(i)$ and we compute its probability density function (PDF). The noise level value should appear as the smallest mode and the most energetic one. Therefore, in order to detect it, we compute the maximum of the PDF. As the threshold is computed relatively to the noise level, the energy difference between signals to be detected has almost no influence.

Cost functions and constraints

In [3], it was supposed that the IF was slowly varying. This assumption remains valid since a lot of signals have a continuous frequency law. The second cost function was defined for the monocomponent signal case. At one instant, all the TF values were sorted and a small penalty was associated for the highest magnitude points and a high penalty for the smallest ones. Alternatively, we will implement a penalty function based on the continuity of the signal power. Namely, we expect that signal power is approximately a continue function, i.e., the component amplitude is similar in successive instants. In this case, the path penalty function γ() is time dependent and could be computed as:

$$\gamma(t;k(t),k(t+\Delta)) = c\frac{\| TF(t,k(t))| - |TF(t+\Delta t,k(t+\Delta))\|}{\| TF(t,k(t))| + |TF(t+\Delta t,k(t+\Delta))\|} \qquad (4)$$

where c is a constant value bounded to the influence of this cost function in the calculation of the overall penalty. This function gives a measure of the relative variation of the amplitude between instant t and $t+\Delta$.

The beginning and the end of the components can be detected by imposing some constraints to the cost functions. It is decided to stop the continuation of a component when the new penalty increment becomes much higher than its average value on the path. In addition, we use the assumption that all the detected maxima correspond to the signal. Therefore, if a maximum has not been used, it will be considered as the beginning of a new component. At the end of the detection process, some noise will be gathered and detected as a signal. But it is easy to classify the resulting signals according to their length and energy. All the post detection processes should then be applied to relevant signals first.

Description of the algorithm :

L *: length of the signal*
$f(c)$ *: penalty function of the path c.*
K *: factor for penalty constraint.*
Γ_i *: optimal paths from start points to C_i points.*

1) *Initialisation*
   set $i_0 \in [1, L]$ *as* $C_{r<i_0} = \{\ \}$ *and* $C_{i_0} \neq \{\ \}$
   Therefore, i_0 *is the first non empty maxima set index. We then define* $\Gamma_{i<i_0} = \{\ \}$, $\Gamma_{i_0} = C_{i_0}$
   $i \leftarrow i_0 + 1$

2) $E_{i,p} = \{(k \cup p), k \in \Gamma_{i-1}\}$, $p \in C_i$
   $E_{i,p}$ *is the set of new path starting from* Γ_{i-1}
   $$\Gamma_i = \left\{\arg\min_{c \in E_{i,p}} f(c),\ p \in C_i\right\}$$

3) $\forall p \in C_i$, *define* c_p *as the optimal path leading to* p *and* $c_{\bar{p}}$ *the same path without p.*
   note that $c_{\bar{p}} \in \Gamma_{i-1}$
   define the average penalty $A = \dfrac{f(c_{\bar{p}})}{length(c_{\bar{p}})}$
   and the penalty increment $I = f(c_p) - f(c_{\bar{p}})$
   if $I > K.A$ *then*
   retain $c_{\bar{p}}$ *as a path*
   $\Gamma_i \leftarrow \Gamma_i - \{c_p\}$

4) *if any* p *of* C_i *remains unused, set p as the start of a new path:*
   $\Gamma_i \leftarrow \Gamma_i \cup \{\{p\}\}$
5) *if* $i = L$ *then retain paths of* Γ_i
   else $i \leftarrow i+1$ *and return to step 2*
   end
6) *Paths are saved*
   RoIs are defined by the paths and the energy spreading associated with each point of the paths.

A light version of the algorithm is presented here for comprehension. With slight modifications, we can tackle the problem of crossing components overlapping in time and frequency by joining them for example. It is also easy to refine detection by adding a priori knowledge to the detector.

5. RESULTS

As an example, the signal depicted on figure 3, is processed. It is composed of four components: two constant frequency pulses and two components with parabolic IF laws which are imbricated. We apply an additive white Gaussian noise to the signal for its SNR to be about 0dB. We used N_f =128 filters. This is the typical example which would make the basic detector (section 2) fail. When plotting the module of the filter outputs, we obtain a kind of short time Fourier transform representation, first part of figure 4. On the second part, we show the result of path detection. The four paths have been successfully detected.

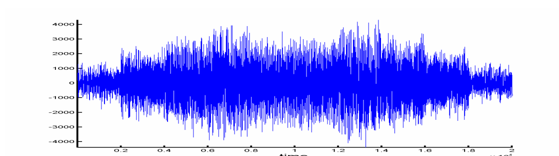

Figure 3. Test signal, SNR=0dB

(a) (b)

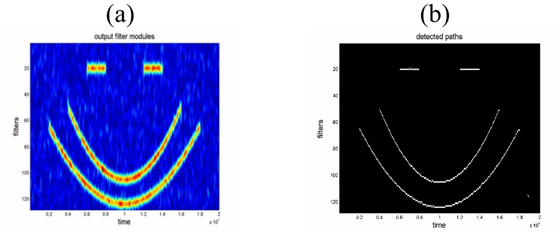

Figure 4. STFT (a) and detected paths (b)

Knowing the paths and the energy spreading of each of its points, it is then possible to give a complete description of the RoIs of the example signal. The detected RoIs are plotted below on figure 5. These data can be used for direct extraction of the detected signals from the filterbank outputs.

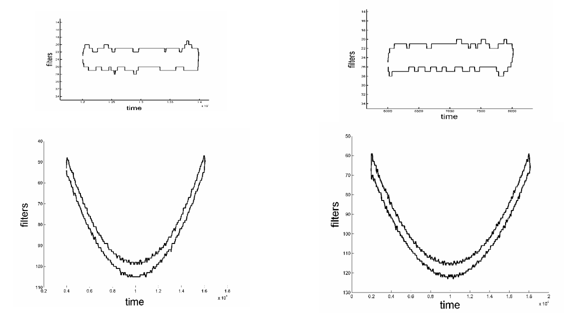

Figure 5. Detected RoIs

6. CONCLUSIONS

In this paper, we presented, a detection algorithm using Gabor filterbank and a Viterbi based grouping algorithm in order to track the TF components. As it is proved by the experimental results, the RoIs detected by the proposed method provide complete and satisfactory information about TF behavior of the considered signals. Consequently, due to its good readability, it may be successfully used for a further feature extraction algorithm. Moreover, this algorithm can be implemented in a recursive manner allowing it to be used in real time processing systems. In further works, we intend to use this algorithm as a feature extraction method in the context of underwater transient signal classification and electronic warfare.

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