INTRODUCTION

The existing algorithms for analysis, synthesis and transformation of sounds ask the users to have a high competence on signal processing. To make the access to these efficient algorithms easier, it is desirable to let the algorithms adapt themselves to the signal and to the transformation needed.

One of the key parameter for nearly all the algorithms which analyze or process the sounds by using time-frequency representations or sinusoidal models is the size of the analysis window; here we show some examples about how this parameter is linked to the resolution of a signal analysis, and which informations can be highlighted choosing a certain size instead of another.

We are at present studying and developing algorithms for the automatic adaptation of the analysis window size. The first method approached is the parallel evaluation of multiple choices automatic adaptation of the analysis window size, modifying $h$ with a time translation of a factor $t$, and a frequency scaling by a factor $\nu$.

We obtain the set $\{h_{\nu,t}(s)\}_{\nu,t\in R}$ where

$$h_{\nu,t}(s) = h((s-t)/\nu).$$

Remark 1

• The Short Time Fourier Transform is the time-frequency transform associated to the set $\{h_{\nu,t}(s)|\nu,t\in R\} \subset L^1(R)$

• Such set contains infinite countable frames of window functions for $L^2(R)$.

A frame can be built by conveniently combining different sets of atoms derived from different window functions. We are particularly interested to the case of the scaling of a same window function, which modifies its time-frequency spread.

$$h_{\nu}(t) = \sqrt{\nu} h\left(\frac{t}{\nu}\right).$$

ADAPTIVE SPECTROGRAM

The spectrogram of a signal $s$ is the squared modulus of the STFT of the signal

$$PS_n(t,\nu) = \int s(t)\overline{\phi}(t) e^{-2\pi i \nu t} dt.$$ (7)

It is always positive and with certain exceptions it can be treated as a probability distribution.

It is possible to perfectly represent the signal $s$ in infinite many different ways, by choosing an appropriate set of multi-index $\Gamma \subset R^n$ so that the relative frame $\{h_{\nu,t}(s)|\nu,t\in R\}$ is dense enough in the time-frequency plane.

where thanks to the features of the Hilbert space $L^2(R)$ we can suppose $\Gamma$ to be countable.

WINDOW FUNCTIONS

We consider a window function as a function $h \in L^2(R)$ such that $|h_0| = 1$ and $h(t) = h(-t)$,

modifying $h$ with a time translation of a factor $t$, and a frequency scaling by a factor $\nu$ we obtain the set $\{h_{\nu,t}(s)|\nu,t\in R\}$ where

$$h_{\nu,t}(s) = h((s-t)/\nu).$$ (5)

Given $PS^N_n$ the spectrogram of a signal $s$ through the frame built on the window $h$, a sparsity measure can be defined to evaluate the energy concentration in the analysis $PS^N_n$:

The notion of best energy concentration is not uniquely defined and is linked to the desired trade-off between time and frequency resolution.

ALGORITHM AND EXAMPLES

• Input and main parameters: the signal $s$, the set of window functions $h_1, ..., h_N$, the Rényi entropy order $\alpha$

• Computation of the $n$ different spectrogram

• Evaluation of the Rényi entropy values on the global analysis

• Choice of the best spectrogram

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**REFERENCES**


