STUDY OF EFFECTS OF THE SHORT TIME FOURIER TRANSFORM CONFIGURATION ON EEG SPECTRAL ESTIMATES

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Abstract: ***EEG signals recorded from scalp contain useful information about the activity of a large number of neurons. Signal processing is needed to extract this information from the EEG signal. Here we study the effects of configurations of Short Time Fourier Transform (STFT) to determine how the parameters of STFT affect spectral estimations of the mean and relative power in beta and gamma frequency bands of the EEG signal. A statistic analysis was performed showing the effects of several window types and window lengths. The estimation of power in a specific frequency band is affected by the configuration of the STFT.***

Keywords: *Electroencephalogram (EEG), Short Time Fourier Transform (STFT), EEG signal processing.*

I. INTRODUCTION

The Electroencephalogram (EEG) is considered a powerful tool in both neuroscience research and clinical diagnosis because it allows to record from the surface of the scalp, electrical signals arising from the brain. One of the important features of the EEG signal is the oscillatory modulation in different frequency bands because oscillations in various bands are associated to various brain processes [1]. The EEG frequency spectrum is divided into several dominant frequency bands: delta (0-4 Hz), theta (4-8 Hz), alpha and Mu (8-12Hz), beta (12-30 Hz) and gamma (30-100 Hz) [2]. To estimate the extent of modulation of the EEG signal in these frequency bands, specialized signal processing tools are required, which are crucial in the process of understanding biological processes underlying normal and pathological brain oscillations.

Here we focus on the beta and gamma frequency bands because these bands are considered to be relevant for the active state, being expressed during wakefulness, cognitive processes, and so on [1]. Increased power in the beta frequency band can reveal that the subject is in an active, busy or anxious thinking and active concentration states. Gamma oscillations are thought to represent the linking between populations of neurons for the purpose to carry out a certain cognitive function [3].

To identify modulations of EEG signal in beta and gamma frequency bands spectral analyses can be used.

In many cases, like here, we need to investigate not only the amount of power in some frequency bands but also the time dependency of the expression of such frequencies along the signal. One of the techniques to analyze non stationary signals, like EEG, is the Short Time Fourier Transform (STFT) that can perform analysis both in time and frequency domain [3].

II. STFT

STFT analysis is one of the most utilized techniques to analyze a signal in time and frequency domain. This technique decomposes the signal into successive window (time frames) to make an estimation of the frequencies present at a particular moment in time. STFT is based on Fast Fourier Transform (FFT), which is a form of the Discrete Fourier Transform (DFT) used for signal processing [4]. A problem with the STFT is in the inverse relation between time and frequency resolutions.

When performing time-frequency analysis it is not possible to have both temporal and spectral resolution at the same time (Gabor limit or Heisenberg-Gabor incertitude principle). Generally, a compromise is made between the temporal and spectral resolution depending on what information is considered to be more important. Here, we analyze the parameters of the STFT for the beta and gamma frequency bands, because, for these bands both the time localization and the power in the EEG signal are important.

Windowing a signal represents a mathematical process of multiplying that signal with a window zero-valued outside of the analyzed interval. This process is used to reduce the effects of the spectral leakage. For the discrete EEG signals DFT is used to estimate the power spectrum for each STFT window [5].Therefore, the frequency spectrum will be divided into frequency bins, whose size is dependent on the length of the window. The effective width of the window determines if there is good frequency representation (smaller frequency bin if the window is larger, contains more samples) or a good time resolution (if the window is smaller, with fewer samples).

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If we have a frame of length N samples, this will give N distinct frequencies that represent the sampling frequency. The more samples (length) the frame window has, the closer the frequency bins lie together, and the smaller the bins are. In turn, if the sampling frequency is increased, but the length is preserved, then the frequency bins will be wider and more distant. Thus, the width of frequency bin equals the sampling frequency divided to the number N of samples within the frame (3). In addition, when for each frame, the DFT is computed using the FFT, the frame length must be power of 2 [4][6].

The power dispersion of the fundamental frequency into the neighboring frequencies is called spectral leakage. The spectral leakage appears when a finite frame length is used for the analysis. Due to use of windowing in STFT, a part of the frame is attenuated at the boundaries. This represents a loss of data in the boundaries regions. Overlapping allows to partly solve this problem because samples from these regions can be recovered. When two consecutive windows contain some common information, an overlapping process is realized. This process uses additional computation power but will give a better accuracy.

III. MATHEMATICAL METHODS

Discrete time Fourier Transform is given by the equation:

$$X(\omega) = \sum_{n} x(n) e^{-j\omega n} \qquad (1)$$

If $x(n)$ is time limited with a duration of N samples (1) becomes:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\omega_k n} \qquad (2)$$

where $\omega_k = 2\pi k/N$ is the discrete frequency of DFT and k is the bin. The central frequency of bin k in Hz will be:

$$f_k = f_s \frac{\omega_k}{2\pi} \qquad (3)$$

The STFT can represent sequences of any length by breaking them into blocks or frames and applying the DFT for each block. If we have N samples we must consider the frame length $M \leq N$. R represents the number of non-overlapping frames of length M the sequence N can be divided to, $N = RM$. If o is the fraction by which the frames will overlap then the overlap in samples is $D = oM$ and the number of overlapping frames of length M is [7, 8] $L = R/(1-o)$

The frames can be represented in fixed time origin as:

$$x_i(n) = x(n + iD) \qquad (4)$$

Where: n=0,..., M-1, i=0,..., L-1, and iD is the start sample of the block i. From (2) and (4) we can create the frame by multiply $x_i(n)$ with the window $w(n)$. The frame's Fourier transform is:

$$X_i(k) = \sum_{n=0}^{M-1} x_i(n) w(n) e^{-j\omega_k n} \qquad (5)$$

From (5) power can be obtained as:

$$P_i(k) = 10\, log_{10}\left(\frac{1}{U} |X_i(k)|^2\right) \qquad (6)$$

$$\text{where } U = \frac{1}{M} \sum_{i=0}^{M-1} |w(n)|^2 \qquad (7)$$

is the normalized power factor of the window [8].

From (6) the power in a frequency band over time can be calculated as:

$$P_i[y,z] = \sum_{k=y}^{z} P_i(k) \qquad (8)$$

where y and z are the inferior and superior limits of the frequency band, in our case $P_i[12,30]$ for beta and $P_i[30,100]$ for gamma.

From (8) we can calculate the mean power:

$$M_{P[band]} = \frac{1}{L} \sum_{i=0}^{L-1} P_i[band] \qquad (9)$$

From (9) M_{P_β} and M_{P_γ}, the mean power in beta and gamma bands can be calculated. For the relative power we will use:

$$I_{band} = \frac{P_{band}}{P_{EEG}} \qquad (10)$$

If we note P_β , P_γ and P_{EEG} the sum of powers across frames, in the beta band and gamma band, and the entire spectrum respectively, from (10), by changing the P_{band} with P_β and P_γ we obtain the relative power in beta and gamma bands I_β and I_γ.

IV. SYSTEM CONFIGURATION

EEG data was recorded using a high density EEG device with 128 active electrodes (BioSemi, ActiveTwo). A 0.5-100 Hz band pass and a 50 Hz notch filter were applied on the raw signal. The sampling frequency was 1024 Hz.

Data from 32 channels was used for these tests from the electrodes placed in the occipital area. For each channel the signal was divided into 350 trials of data.

MATLAB environment processing tool was used to process signals. Multiple window types and window lengths were tested to identify the effects of the STFT's configuration on spectral estimates. The tested window types were *Hamming*, *Gaussian*, *Hann* and *Bartlett-Hann* with lengths of 128, 256, 512 and 1024 samples. The overlap value for these tests was 96% of the frame window.

V. RESULTS

The first part of this session describes the effects of the narrowband and wideband transforms (see narrowband and wideband spectrogram) on the EEG spectra. A wide window length gives better frequency resolution but poor time resolution. A narrower window gives good time resolution but poor frequency resolution.

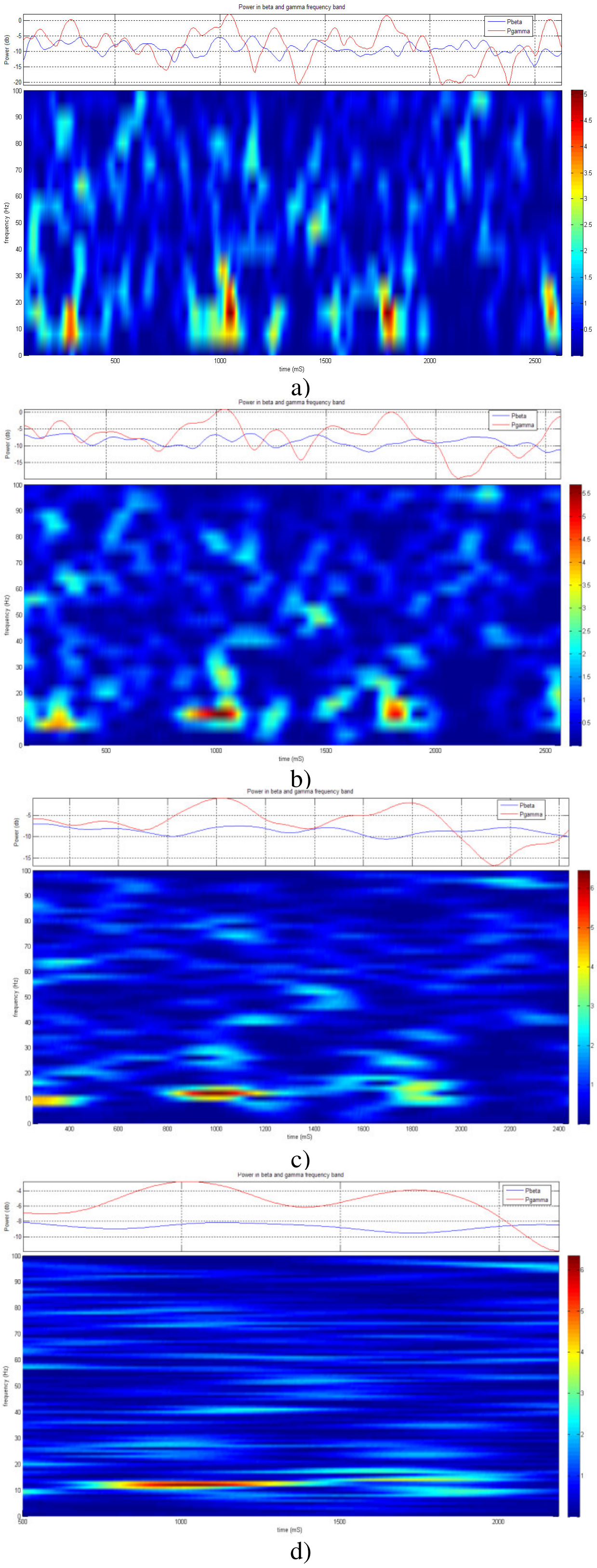

Figure 1. STFT estimation for one EEG trial. Each panel contains two parts: the upper part represents the power in beta and gamma bands and the lower part the STFT transform. The frame lengths are 128 (a), 256 (b), 512 (c), and 1024 (d).

Analysis was performed on one trial of EEG signal, using frames with *Hamming* window, of different lengths.

From *Figure 1* we can see the influence of the frame length over the time and frequency. As shorter windows there is a better representation of the signal over time (*Figure 1* a, b), while with long windows there is a finer representation in the frequency domain (*Figure 1* c, d).

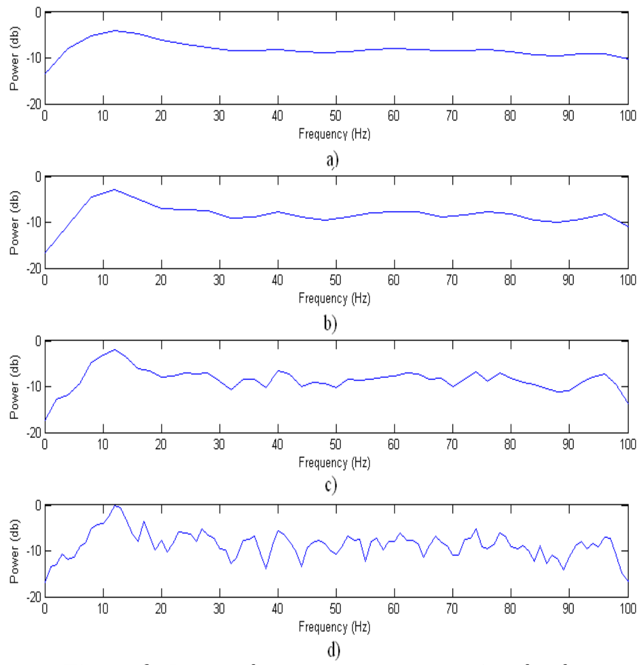

Figure 2. Power-frequency representation for frame length: a) 128 (125 ms), b) 256 (250 ms), c) 512 (500 ms), d) 1024 (1000 ms)

The same effect is also visible in the periodogram (Welch's periodogram) represented in *figure 2*. Again, we observe a finer representation of the frequencies when the window length is higher and a smoother one when the frame length is smaller. Due to the relation between maximum frequency and the frequency bin (frequency as discussed earlier), more and narrow frequency bins will give a better frequency resolution, fewer and wider ones will give less frequency resolution.

The second part of the study is a statistical analysis of several window types.

The statistical analysis was performed on 32 EEG channels, a total of 62 trials, 1-3 trials for each channel of the EEG signal. For each window length and window type, we analyze the mean ($M_{P_\beta}, M_{P_\gamma}$) and relative (I_β, I_γ) power in beta and gamma.

In these analyses we wanted to assess how spectra estimate change when different window types are used. We wanted to investigate which window type has the maximum influence over the mean and relative power in the beta and gamma bands.

The values from the *Table 1* represent percentages of cases across trials where one window type yielded maximum value compared to the other window types for the mean powers $M_{P_\beta}, M_{P_\gamma}$ and relative powers I_β , I_γ.

Frame length	Window Type	M_{P_β} (%)	M_{P_γ} (%)	I_β (%)	I_γ (%)
128	Hamming	100.00	12.90	100.00	16.13
	Hann	0.00	69.35	0.00	70.97
	Gaussian	0.00	16.13	0.00	12.90
	Bartlett-Hann	0.00	1.61	0.00	0.00
256	Hamming	90.32	25.81	90.32	27.42
	Hann	4.84	59.68	4.84	58.06
	Gaussian	0.00	11.29	0.00	9.68
	Bartlett-Hann	4.84	3.23	4.84	4.84
512	Hamming	62.9	30.65	70.97	45.16
	Hann	14.52	25.81	19.35	25.81
	Gaussian	19.35	43.55	9.68	25.81
	Bartlett-Hann	3.23	0.00	0.00	3.23
1024	Hamming	58.06	51.61	51.61	45.16
	Hann	19.35	25.81	24.19	24.19
	Gaussian	22.58	17.74	24.19	29.03
	Bartlett-Hann	0.00	4.84	0.00	1.61

Table 1. Statistics on the influence of the window type over the relative and mean power in frequency bands.

This distribution was repeated for several window lengths. Values in *Table 1* indicate that the same window type yields different results in different frequency bands and with different window lengths. We can see an increased in power in beta frequency band using *Hanning* window while in gamma frequency band can be seen an increased in power using *Hann*, *Gausian* or *Hamming*, depending on the window length.

Frame length difference	Window Type	M_{P_β} (db)	M_{P_γ} (db)	I_β	I_γ
128-256	Hamming	-0.249	0.068	0.051	-0.031
	Hann	-0.276	0.076	0.048	-0.032
	Gaussian	-0.269	0.074	0.049	-0.032
	Bartlett-Hann	-0.267	0.074	0.049	-0.032
256-512	Hamming	-0.023	0.004	0.034	-0.015
	Hann	-0.035	0.006	0.033	-0.015
	Gaussian	-0.033	0.005	0.033	-0.015
	Bartlett-Hann	-0.031	0.005	0.034	-0.015
512-1024	Hamming	0.134	0.072	0.008	0.004
	Hann	0.132	0.073	0.008	0.003
	Gaussian	0.134	0.074	0.008	0.003
	Bartlett-Hann	0.133	0.073	0.008	0.003

Table 2. The mean amplitude difference between two frame lengths having the same window type

Finally, we calculate the difference between corresponding mean powers $M_{P_\beta}, M_{P_\gamma}$ and relative powers I_β , I_γ computed for windows with consecutive lengths. The values from *Table 2* represents the power difference between the same window type of two consecutive frame length.

As can be seen, there are differences in power between window lengths, in some cases the power value increases as the window length is increasing, whereas in some other cases this trend is reversed.

VI. CONCLUSIONS

The power in a frequency band is influenced in a different way, depending on frequency band and of window type. As can be seen, the *Hamming* window increases the power in frequencies from the beta frequency band, while *Hann* and *Gaussian* will increase power in gamma band.

The window length also influences the power, but this influence is in general both nonlinear and nonmonotonic. The window should be chosen considering the frequency bands of interest, as it can drastically influence the results when estimating EEG signal spectra.

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