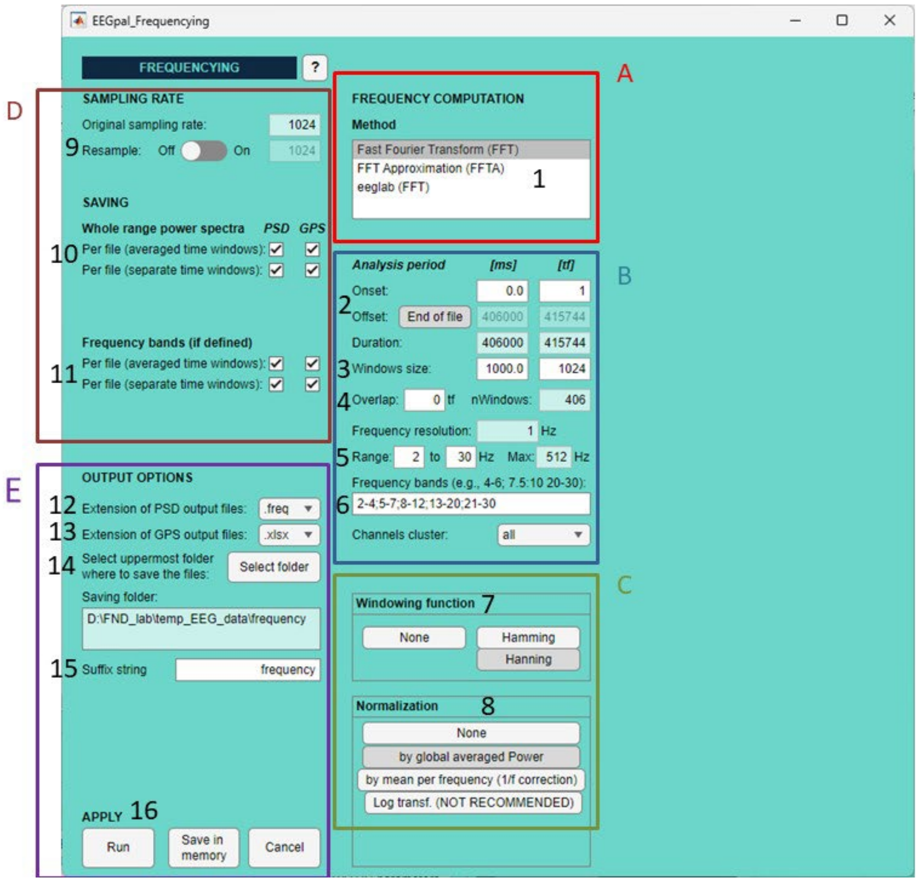
EEGpal: **Frequencying module**

Version 2.01, 20.11.2025

Video tutorial: https://youtu.be/YpH4a4mQz38

The 'Frequencying' module can be used to performed frequency analysis in the EEG signal. This type of analysis is often used to find biomarkers of pathologies (e.g. using a resting state recording). The output of this toolbox is the **power** for a given frequency (unit : $\mu V^2/Hz$). This power represents the amount of energy contained in these frequencies. In other words, it tells you how much these frequencies contribute to the EEG signal in the time domain. You can choose to calculate this value for each electrode separately (corresponding to the Power Spectral Density [PSD]) or to have an average/global value for your EEG signal (corresponding to the Global Power Spectrum [GPS]). This calculation is done thanks to the Discrete Fourier Transform (see FAQ for more details).



Pannel A:

1. Choose the method to apply for the frequency analysis:
    a. The Fast Fourier Transform (FFT) is the traditional method. It provides a positive power in any case. This is sufficient for classical GPS analysis.
    b. An FFT approximation (FFTA) is required for an inverse solution (IS) analysis or topographical analysis at your frequency. More details can be found in the FAQ.

   c. eeglab (FFT), permit to use the *newtimef* function of eeglab to compute the FFT and perform the time-frequency analysis (see FAQ for more details about its functioning).

Pannel B:

2. Select the part of the signal on which you want to perform the frequency analysis (onset = start point and offset = end point). Reminder: [ms] = millisecond, [tf] = time frame, End of file = automatically selects the end of the file as offset.
3. **Windows**: To perform the frequency analysis, the original signal is divided into several windows. The output is a power value for each window, which allows us to see how it evolves over time.
   Please specify the window size (time length). Note: This parameter determines the frequencies that can be studied (see FAQ for more details).
4. **Overlap**: You can reduce the distance between two windows by allowing them to overlap. For example, if you have two windows, each with a TF value of 100, and you specify an overlap of 20, the next window will start at 80 instead of 100. This is mainly to artificially increase the temporal resolution of our frequency analysis in the case of a short recording.
5. **Frequency range to study**: This is where you specify the frequency range to be examined in your analysis. The upper limit should not exceed the maximum frequency displayed in the GUI. The frequency resolution informs you of the minimum distance between two frequencies that will be evaluated.
6. **Frequency bands**: If you are interested in specific frequency bands (e.g. alpha = 8-12 Hz, beta = 13-30 Hz), you can specify them here. Please respect the typography by using '-' to separate the upper and lower limits and ';' to separate the frequency bands (e.g. 8-12;13-30).
   Warning: The specified frequency bands must be within the frequency range specified in point **5**. You cannot specify a band 13-30 if you have specified a frequency range of 0-15.

Pannel C:

7. Choose the Windowing function between None, Hamming or Hanning. This option is available only for classical FFT and FFTA. In eeglab FFT, the Hanning is selected by default. For more information, please read the FAQ section.
8. To make the comparison between individuals or groups easier to interpret, you can normalise the power value obtained (for more detail, please consult the FAQ).
   a. **By global averaged Power**: Divide the power of each frequency by the mean power across all frequencies defined in point **5**. The result will be the frequency distribution relative to the mean power. For example, a value of 0.8 means that the power at this specific frequency is 80% of the average power.
   b. **By the mean per frequency (1/f correction)**: The power of each frequency is divided by the mean power of that particular frequency across all the electrodes. This flattens the power distribution across frequencies, correcting for the higher power found in low frequencies compared to high frequencies.
   c. **Log. Transf.**: Similar as previous 1/f correction in $\log_{10}$ (similar as EEGLAB). This is not recommended due to strange result and literature (look at the FAQ for more details).

Pannel D:

9. **Resample the data**: You can resample your data at a different sampling frequency (the new frequency must be specified in Hz). This is usually done when you want to reduce the

sampling rate.
WARNING: If you are using this option, please go through and check point **2-6,** as these will affect their values.

10. **Choose the output to save**: You can select the power to be stored for the frequency range specified in point **5**. The PSD provides the Power Spectrum Density for each EEG electrode and for each individual frequency within the specified range. The GPS provides the Global Power Spectrum which is an average of these frequencies across all the electrodes. There are two options:
    a. Per file (averaged time windows): Average the frequency power over all the time windows
    b. Per file (separate time windows): Record the frequency power for each time window. This is useful if you want to study the evolution over time.

11. The same option as described in point **10**, but for the frequency band you have specified in step **6**. These options are only available if you have entered a frequency band of interest.

Pannel E:

12. Select the format for the PSD output files. Files with the .freq extension can be opened in Cartool. Otherwise, you can save them as a Matlab variable (.mat).
13. Select the format for the output files for the GPS output (.xlsx, .csv or .ep file).
14. Select the destination folder where the results files will be saved (note: it will automatically create a sub-folder call *Frequencying*).
15. The suffix added to the input filename to obtain the output filename
16. There are three validation buttons:
    a. The **Run** button will carry out the processing parameterized in the Frequencying module.
    b. The **Save in memory** button will store all the parameters in memory and close the Frequencying module without performing the processing.
    c. The button **Cancel** closes the module without processing and without keeping the entered parameters in memory. The same effect will be achieved by closing the Frequencying module window.

FAQ

What is the Fast Fourier transform (FFT) and how can frequency power be computed from it?

The Fourier transform (FFT) allows a signal in the time domain to be transformed into the frequency domain. In the time domain, the amplitude of a signal directly reflects variations in voltage over time (for example, microvolts in an EEG). When we move to the frequency domain using the FFT, this temporal amplitude is translated into an amplitude for each frequency. A frequency with a large amplitude in the frequency domain indicates that it contributes significantly to the total signal in the time domain.

When you apply the FFT to an EEG signal (or any other signal), you break it down into a sum of sinusoids of different frequencies. For each frequency, the Fourier transform gives a *complex coefficient* (for example a+b*i where a in the real component [Re(X(k))] and b is the imaginary component [Im(X(k))] that represents that frequency in the original signal. This complex coefficient has an *amplitude* (or modulus) and a *phase*. To compute this frequency amplitude, we can compute the norm of the complex vector with the following formula:

$$\text{Amplitude} = |X(k)| = \sqrt{\text{Re}(X(k))^2 + \text{Im}(X(k))^2}$$

The *power of a frequency* is a measure that describes the amount of energy contained in that particular frequency. It is calculated by taking the *square of the amplitude* of that frequency (i.e. the square of the magnitude of the coefficient in the frequency domain).

Formellement :

$$\text{Puissance de la fréquence} = |X(f)|^2$$

où $X(f)$ est le coefficient complexe pour la fréquence f dans la transformée de Fourier, et $|X(f)|$ est son module (ou amplitude).

The last step is to divide this power by the size of temporal segments (N) to obtain the *average power per unit time* for each frequency. This operation normalizes the power, making it comparable between different epoch lengths or between different segments of the signal.

$$\text{Puissance de chaque fréquence} = \frac{|X(f)|^2}{N}$$

What is the difference between the FFT and the FFTA, and when should the FFTA be used?

The problem with the classical FFT is that you lose the polarity information needed to compute an IS. This is why Brunet et al. (paper: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3022183/) proposed a way to restore the polarity information between the electrodes. It is the famous FFTA introduced in the Cartool software. In fact, the reconstructed polarity is random and an electrode can be positive on one map and negative on another. To solve this problem, Cartool will use the polarity of the first map to correct all the others (to have the same polarity everywhere). MichaelDP improved the concept by looking for the best map to use as a reference by studying the maps that correlate the most.

Why does the choice of window length affect my frequency analysis (point 3)?

The highest frequency you can analyse is always half the window length. For example, if my window is 1000 ms, the maximum frequency of my analysis will be 500 Hz (in the case of a sampling rate at 1000Hz). This is because of the Nyquist theorem. The maximum frequency is shown in the interface at position 5.

What is the windowing function and why should I use it (point 7)?

During frequency analysis in EEG, we cut the signal in several time window which introduce discontinuities. The use of a *windowing* function may be necessary to reduce the undesirable effects associated with discontinuities at the edges of the signal when calculating the Fourier transform. These discontinuities manifest themselves as 'edge artefacts' that create undesirable effects in the power spectrum, in particular the phenomenon of '*spectral leakage'*, where the energy of a given frequency 'leaks' towards adjacent frequencies.

Spectral leakage occurs mainly because of discontinuities at the ends of a signal segment. When performing a Fourier analysis on a finite time segment, it is implicitly assumed that the segment is periodic (that it repeats ad infinitum). If the start and end values of the segment do not match, a discontinuity is created, introducing high frequencies that are not present in the original signal.The consequence could be :

- Dispersion of energy over several frequencies: Instead of being concentrated on the frequency of interest, the energy 'leaks' into neighbouring frequencies, making the peak less clear and making it difficult to identify certain frequencies accurately.
- Difficulty in detecting nearby frequencies: In an EEG signal, where you want to analyse narrow frequency bands (alpha, beta, etc.), spectral leakage can mask details and make it difficult to distinguish between nearby frequencies.
- Bias in the power spectral density (PSD): As the energy is not strictly localised on the expected frequencies, the measurement of the power of the frequency bands is less reliable.

The windows function search as Hamming or Hanning will modulate the amplitude of the signal in the time domain (before FFT computation) to decrease the contribution of windows edge. For example, if I have a 1024 TF window, we'll multiply the data by a vector [0.08, 0.08,...,1,...,0.08) for Hamming windowing.

The disadvantage of applying a windowing function is that it artificially reduces the amplitude at the ends of the signal, which can reduce the power measured in the frequency bands, as it attenuates the signal in the time domain before moving on to the frequency domain. To compensate this lost of power, you can normalize the powers according to a reference period or a reference frequency as suggested in point 8.

Sould I use a hamming or an hanning window function (point 7)?

For EEG frequency analysis in the 2-30 Hz spectrum, the Hamming and Hanning windows are both good options for reducing spectral leakage, but they have slightly different characteristics that can guide the choice according to the precise objectives of the analysis:

1. *Hanning window:*

  - This window offers progressive attenuation at the ends of the segment, making it very effective at limiting spectral leakage.
  - It has better control of near frequencies, but with a wider central lobe than the Hamming window.
  - Hanning is particularly suitable if the aim is to isolate relatively narrow frequency bands accurately, such as the alpha and beta bands in EEG, while minimising leakage.

2. *Hamming window:*
  - This has a slightly different shape and offers a better compromise between leakage attenuation and central lobe width, which improves frequency resolution (i.e. the ability to discriminate frequency peaks).
  - It attenuates the edges less, which reduces the loss of information at the edges and can be an advantage if you have a long-duration signal.
  - Hamming is often preferred if you're looking to balance leakage and frequency resolution, especially when you're interested in slightly wider frequency bands.

Conclusion

For a broad spectrum such as 2-30 Hz in EEG:

- *Hanning window*: preferred if you are looking to minimise spectral leakage, particularly for narrow bands.
- *Hamming window*: recommended if frequency resolution is important, with a slight compromise on leakage.

In practice, the two windows give similar results for EEG analysis, but if you are working with very close bands (for example, a fine separation between alpha and beta), the Hanning window may be slightly more appropriate.

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Should I normalize my power values (point 8)?

Whether or not to normalize power values depends on your specific goals and the type of analysis you're performing. Here are some cases where normalization is often recommended and how it can improve the interpretability of your power results:

Comparing Across Participants or Trials

- *Why Normalize?* Individual differences (e.g., baseline power or amplitude differences between participants) can make it difficult to compare power values across participants or sessions.
- *How to Normalize?* You can normalize power within each participant, often by dividing by the total power (option *by global averaged Power* in point 8)

Comparing Power Across Different Frequency Bands

- *Why Normalize?* Power values naturally tend to be higher in lower frequency bands due to the 1/f property of EEG signals (where lower frequencies have higher power). Normalizing helps account for this, especially if you're interested in comparing higher-frequency bands (e.g., alpha or beta) to lower-frequency bands (e.g., delta or theta).

- *How to Normalize?* Some approaches include normalizing each frequency band by the average or baseline power in the entire signal or by using a 1/f fit to flatten the power spectrum (option *by mean per frequency (1/f correction)* in point 8.

In addition, Log-transforming power values (e.g., log10) can reduce the skew from extreme values and is often used in EEG power spectral analysis to make distributions more normal. The formula is

LogPower = 10 .* $\log_{10}$(Power ./ mean power);

However, this normalization has been criticized in the paper:
https://pmc.ncbi.nlm.nih.gov/articles/PMC8354524/

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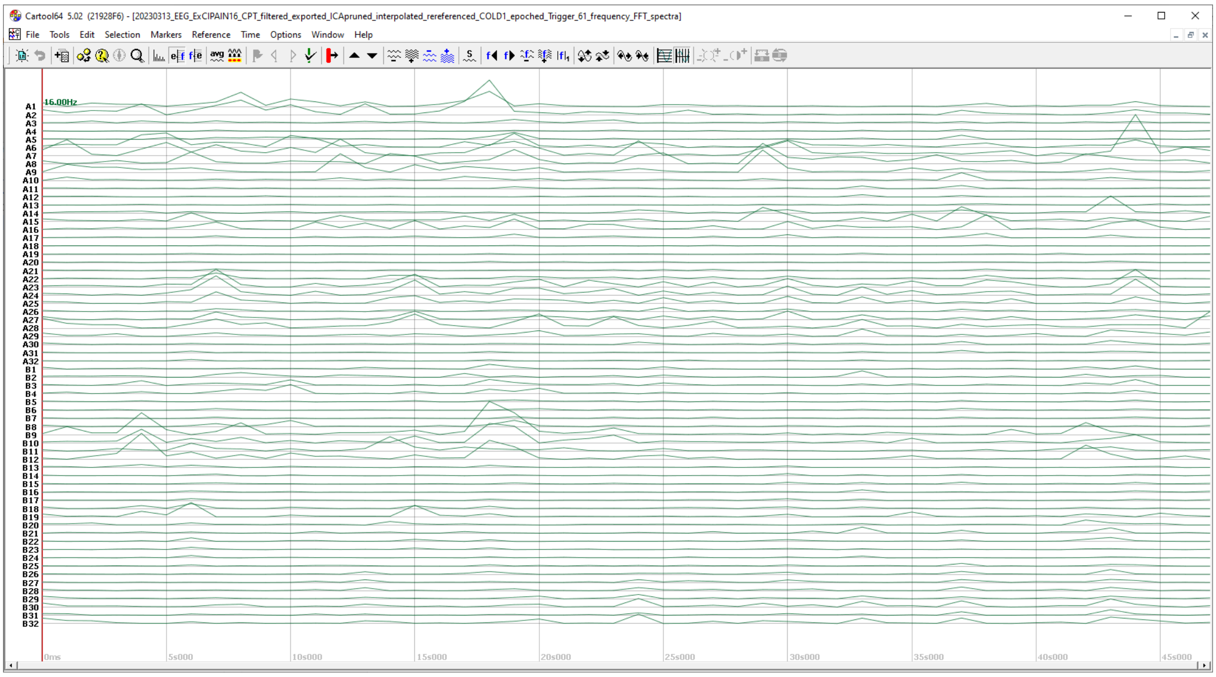
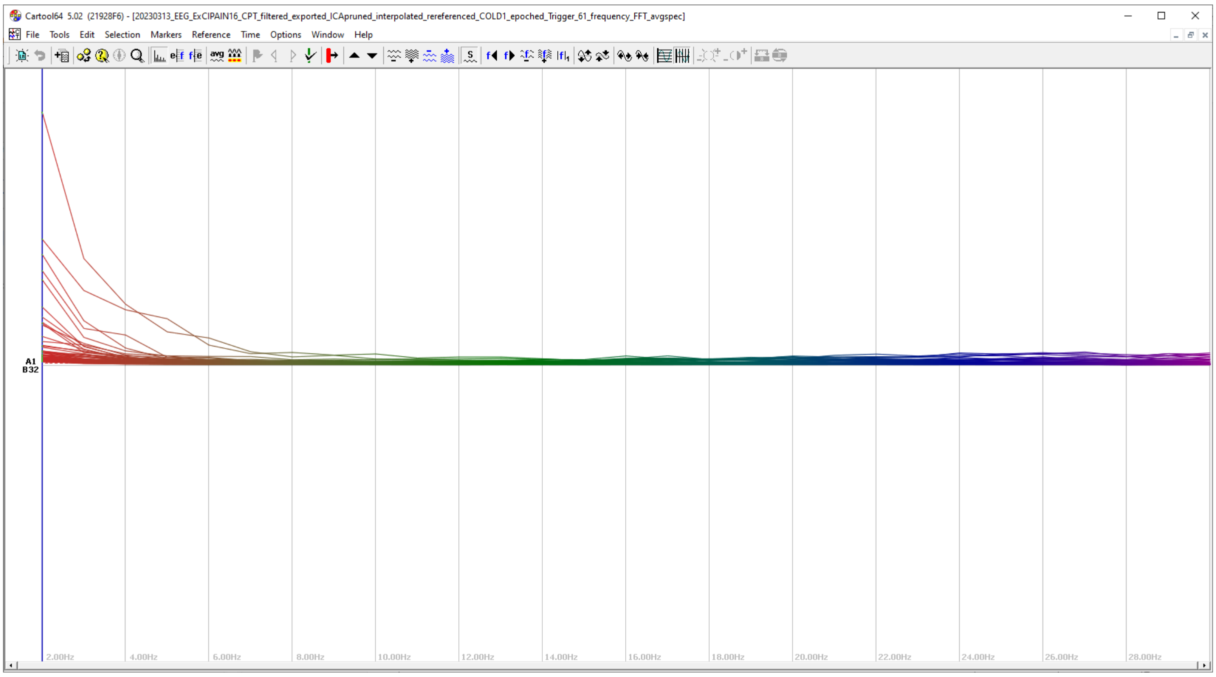
How can I display my result .freq file in Cartool?

In the case of 'Per file (separate time windows)' option from point 11



By default, Cartool show you the result for a specific frequency (in this example 16Hz) with the power for each time windows (horizontal dimension) and the electrodes (vercital dimension). To change the frequency to displayed, use the button : 

In case of 'Per file (averaged time windows)' option :



By default, Cartool show you the Power spectrum view. Each line is the average power across each time window for each electrode. The horizontal axis is the different frequency of the spectrum.

In both cases, you can associate the file with a coordinate file to have an estimation of the topography (in a lm file) as usual. The manipulation of the power trace is also similar as in EEG file display.

How can I interpret the PSD output .mat file ?

The output PSD .mat files don't have header to help you to understand how the data are organized. However, you can interpret the organization by looking at the matrix dimensions. Here is the organization of the output matrixes:

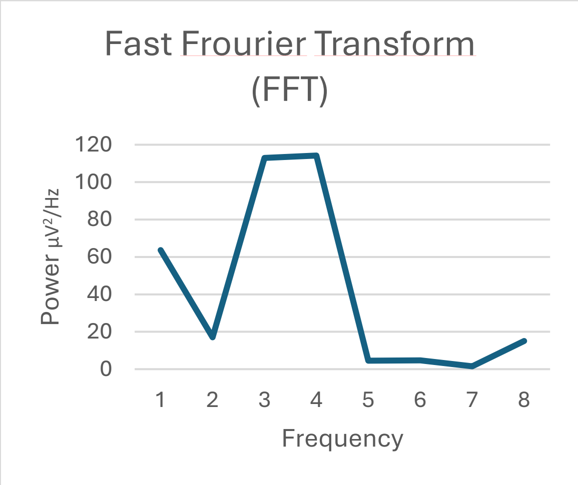
- *PSD whole range (averaged time windows*) : # of frequency bins **X** # of electrodes
- *PSD whole range (separate time windows*) : # of frequency bins **X** # of electrodes **X** # of windows
- *PSD Frequency bands (averaged time windows*) : # of frequency bands **X** # of electrodes
- *PSD Frequency bands (separate time windows*) : # of frequency bands **X** # of electrodes **X** # of windows

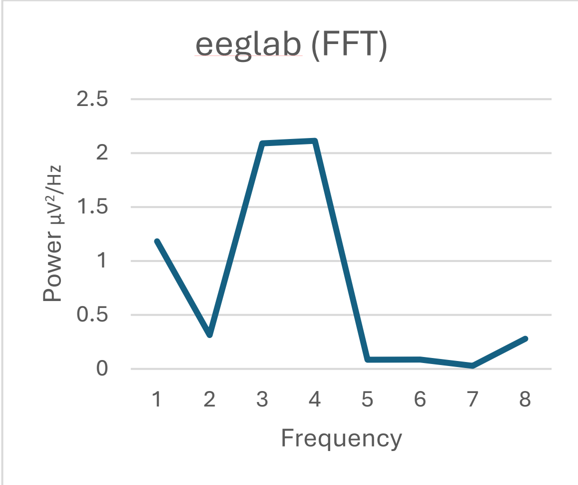
Can I study some specific electrodes instead of all?

Yes, you can specify with which electrodes you want to work. You have to specify them before to open the *Frequencying module*. In the main EEGpal windows, press on the button *Electrode Setting*. After selecting of the appropriate 'Electrode Setting file', select the electrodes that you want to include in the analysis (column *include*) and press on Done button. Then when you will open the *Frequencying module* only the electrodes that you have selected will be studied.

Is there a difference of results between 'Fast Fourier Tansform (FFT)' and 'eeglab (FFT)'?

The two options are similar according to the change of power between the frequencies (see plot below). However, there is a difference of scaling in the power value even if both results have the same unit (μV^2/Hz).





Should I use the option 'Fast Fourier Tansform (FFT)' and 'eeglab (FFT)' in point 1?

Difficult questions. The option *Fast Fourier Tansform (FFT)* use the standard FFT function of Maltab which is well established. It offers also more flexibility for the windowing options (point 7).
The advantage of the option *eeglab (FFT)* is that the function developed by Arneud Delorme is well establish in EEG community and used in many papers.
At the end, the statistical results should not be too different.

How is the eeglab command works?

The important command is *newtimef* (see its help for details). I will present here the arguments that I have decide to use in the interface of EEGpal. Here is a practical example:

ersp(:,:,i) = pop_newtimef(EEG, 1, i, [0 350999], 0 , 'baseline',NaN, 'freqs', [8:0.666:13], 'scale', 'abs', 'ntimesout', 234, 'winsize', 1536, 'plotersp', 'off', 'plotitc' , 'off', 'plotphase', 'off');

input:

- EEG : input data struct in eeglab format
- 1 : frame per trial (ignored)
- i : the indice of the current electrode studied
- [0 350999] : the onset and offset time point in ms that you want to study (point **2**)
- 0 : This parameter permit to study the power with FFT. The function allow you to use a wavelet decomposition instead (if you use a value of 1 or 2, see https://www.youtube.com/watch?v=eUFf5eFpdLg). This option is not integrated inside of EEGpal. To use it, you have to pass by the GUI from eeglab ("Plot->Channel time-frequency").
- 'baseline',NaN: Deactivation of any baseline correction
- 'freqs', [8:0.666:13]: The vectors of frequencies which will be studied (point **5**)

- 'scale', 'abs': Force to keep absolute value and not dB ($10\log_{10}(x)$) values
- 'ntimesout', 234: Number of windows (point **4**)
- 'winsize', 1536: window size in TF (point **3**)
- 'plotersp', 'off', 'plotitc' , 'off', 'plotphase', 'off': Deactivation of eeglab plots.

Output

- ersp: Event-Related Spectral Perturbation (FFT), frequencies X time-windows