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Application of Hanning-Based Short Time Fourier Transform in Localization of Imagined Motor Movement within Human Brain

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***Abstract*— This paper intends to present a multi-disciplinary series of research and results in the field of computational neuroscience and signal processing investigating the localization of fine motor movement of the hands within the human brain using Joint Time-Frequency Analysis, and more specifically, Hanning-windowed Short Time Fourier Transform (STFT). Datasets used for analysis were generated using electroencephalography (EEG) data collected from human test subjects. This paper shall discuss the mathematical analysis that was conducted, the experiment used to collect the data, signal pre-processing, epoching of data, and analysis conducted using EEGLab and Matlab. Furthermore, this paper presents the use of the STFT and spectrogram to aid in the search of enhanced correlation between motor movement of the human phalanx (proximal, medial, and distal) and a more definite region of the primary motor cortex.**

***Index Terms*— Electroencephalography (EEG), Event Related Potential (ERP), Short Time Fourier Transform (STFT), Spectrogram, Hanning, Computational Neuroscience, Joint Time Frequency Analysis, Signal Processing**

I. Introduction

The electroencephalogram, or EEG, is a commonly used medical test that records a patient's brain activity during a period of time. By instrumenting the scalp of the patient undergoing analysis, electrical impulses are recorded and analyzed in an effort to identify changes in brain activity that are indicative of potential neurological illnesses and diseases [8][13]. Since motor neurons are constantly communicating along the nervous system, the EEG is an excellent test for measuring human task load index (TLX) as well as other neurophysiological motor functions. As the brain is the primary processor of neurological biopotentials, the EEG is a widely used tool for analyzing human function as well as diagnosing or treating illnesses such as brain tumors, epilepsy, sleep disorders, dementia, etc. [6][8][9][17].

Although the EEG can provide insight into neurological disorders, it can also provide insight into human performance and cognitive behavioral tendencies. Furthermore, the use of the EEG as an informational source for smart prosthetics or other bioinstrumentation technologies is an emerging application [2][8][11]. This paper investigates the analysis of EEG datasets to isolate fine motor movement within the brain using numerical analysis techniques such as the Short Time Fourier Transform (STFT), spectrogram, and power spectral density (PSD) using computational software such as Matlab and EEGLab [5][7]. This window into an area of the brain responsible for fine motor movement is significant because the aforementioned techniques provide a computationally efficient way to provide finer localization resolution into imagined motor movement. This presents an opportunity to instrument the brain and provide a denser, richer source of data to provide to smart prosthetics [2][17].

One key analytical method used in the research work presented in this paper is the joint time frequency analysis tool called the STFT. Joint time frequency analysis (JTFA) aims to provide the user insight into the time and frequency information of a signal and can be categorized into two main categories; STFT and wavelets [6][9]. This paper intends to focus on the STFT. Often, EEG datasets as well as other neurophysiological tests such as the EMG and EKG are represented using voltage as a function of time. This results in a non-stationary signal that is time varying and changing as data is being collected.

This time domain representation, in the case of the EEG, shows excellent time resolution but tells the user very little regarding the frequency component of the signal. Conversely, working with the signal purely in the frequency domain (when using the Fourier Transform) also has challenges, namely due to the EEG signal being non-stationary in nature and having important characteristics represented in the time domain as well as the frequency domain. As this time-varying signal changes over time, the user is unable to clearly detect these changes when working in the pure frequency domain. With this complex nature of data provided by the EEG, it is imperative that data is displayed in a fashion such that frequency and time information can be adequately preserved and analyzed simultaneously.

Datasets collected for the purposes of this paper focused on trials where subjects were asked to imagine movement of the left and right hand with focus on the thumb and forefinger [3]. These datasets were then analyzed using the STFT as mentioned above which resulted in a novel method for isolation of fine motor movement in the human brain using the Hanning-based STFT as well as associated analytical techniques such as PSD and the spectrogram [5][7][10].

II. Short Time Fourier Transform

Two frequently used techniques, both commonly classified as types of JTFA are the STFT as well as the wavelet transform [6][9]. In particular, the STFT provides to be useful in the analysis of non-stationary biopotentials signals such as the EEG thus it was deemed judicious to investigate it’s use in this application.

To establish the analytical foundation of this paper, we can begin with the definition of the STFT by first investigating the trivial form of the Fourier Transform. The Fourier Transform provides a way to represent a time-based signal in the frequency domain, which is representing the sinusoids and their specific composition that comprise the signal undergoing analysis [19]. The Fourier Transform can be defined as

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft}\, dt \qquad (1)$$

where f is the frequency (in Hertz) and $x(t)$ is the time-domain waveform undergoing analysis. $X(f)$ is then the frequency spectrum containing magnitude and phase information of the original time-domain signal. It is therefore clear that this transform to the frequency domain does not tell the user much about the times at which particular frequencies occur within the signal, therefore it is reasonable to assume there is no real usable resolution of a time component.

Since time-varying signals are continuous in nature, like in the case of the EEG, it is fair to assume that the Fourier Transform of a signal over its entire time interval is equivalent to applying a window over a smaller portion of the continuous signal due to it’s associative nature. This piecewise form of the Fourier transform utilizing concepts of windowing and summation over the length of the signal undergoing analysis is known as the STFT [9].

To accomplish this, one must multiply the above signal by a windowing function of which there are several commonly used types (Rectangular, Bartlett, Hanning, Hamming, Blackman, Gaussian) [19][20]. This multiplication of a generalized windowing function $w(t-\tau)$ results in the following function [1][4].

$$G(f,\tau) = \int_{-\infty}^{\infty} g(t) w(t-\tau) e^{-j2\pi ft}\, dt \qquad (2)$$

where $G(f,\tau)$ is the STFT and $w(t-\tau)$ is the interval by which the window is shifted. The purpose of this window is to suppress the signal undergoing analysis, namely $x(t)$ outside the desired, windowed, region. Therefore the Fourier Transform is computed for that particular window which yields a signal-significant local spectrum.

As mentioned above, several window types can be utilized when computing the STFT [19]. Although any square-integrable window is computationally sufficient, some windows offer features that offer more computational incentives than others for the desired application. These windows have simple functional forms that make the Fourier Transform computation efficient and significantly less demanding. It is important to note that if the window selected is that of the Gaussian function, it is called the Gabor Transform. The Gabor Transform is a special case of the STFT named after Dennis Gabor, which involves the use of the Gaussian function as the windowing function when computing the STFT.

During the course of this research work (discussed in the “current work” section of this thesis proposal), a Hanning window was selected. The Hanning window was selected due to the nature of the data being analyzed, namely that of EEG datasets. The Hanning window is a suitable STFT windowing function for examining EEG signals since it is characterized by its good frequency resolution and minimized spectral leakage. The Hanning window was selected due to its tendency to “smooth” data and returns a friendly frequency representation of the signal undergoing analysis [20]. The following function represents the Hanning windowing function [20]

$$w(t) = \begin{cases} 1(1-\cos(2\pi t))/2, & 0 \le t \le 1 \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

After applying the STFT using a windowing function, the result is a Fourier Transform that is simultaneously a function of time as well as of frequency, which allows analysis of time and frequency components concurrently [1]. A window with a shorter interval allows for more resolution in time because there is a higher number of samples of which the Fourier Transform is being computed. There is, however, a tradeoff when selecting window size. Too wide of a window can result in lower time resolution since infinitely expanding the window in Equation (2) will result in the following scenario

$$w(t-\tau) = w(t) = 1 \qquad (4)$$

For which we can see that we are simply left with the standard definition of a Fourier Transform that lacks any meaningful time information. Conversely selecting an infinitely small window expectedly results in good time information without any meaningful frequency resolution [20]. This uncertainty can be written as

$$\Delta t \Delta f \geq \frac{1}{2\pi} \qquad (5)$$

Where Δt represents time resolution while Δf is the resolution for the frequency term. This provides a limiting relationship regarding both time and frequency analysis.
This mathematical approach, when applied to large time-varying datasets such as EEG epochs allows resolution in both the time and frequency domain. Not only can we see how the signal changes over time (from the time domain portion of the analysis), we can also see at what times the frequencies occur. By conducting the analysis on a series of clinical EEG dataset, it is proposed that a spectrogram can provide useful in localization of fine motor movement within the brain.

III. Spectrogram

The spectrogram is a visual representation of the STFT as discussed previously [1]. As mentioned previously, a window of varying shape is applied to a time-varying signal. The Fourier Transform is calculated at that window before the window is shifted to a $t+1$ state and recomputed for the following segment of the signal. For each iteration of the Fourier Transform, as defined by the windowing function, a frequency distribution is computed based on a median time. The collection of this frequency distribution is plotted in a 2D visual representation as time versus frequency with frequency now being the dependent variable.

In many cases when computing the STFT, it is necessary to generate a visual tool for qualitative analysis to corroborate the numerical methods discussed above. The spectrogram allows the user to plot signal energy over time in particular frequency bands by squaring the magnitude of the STFT. This allows analysis of the time-varying frequency content of a signal. The following equation represents the mathematical representation of the spectrogram $S_x(f,t)$ [20]

$$S_x(f,t) = \left|G(f,t)\right|^2 = \left|\int_{-\infty}^{\infty} g(\tau) w(t-\tau) e^{-j2\pi f\tau} \, d\tau\right|^2 \qquad (6)$$

This mathematical approach, when applied to large time-varying datasets such as EEG epochs allows resolution in both the time and frequency domain. Not only can we see how the signal changes over time (from the time domain portion of the analysis), we can also see at what times the frequencies occur. By conducting the analysis on a clinical EEG dataset, it is proposed that a spectrogram can provide useful in localization of fine motor movement within the brain by observing activations and present frequencies.

IV. Data Collection

Data used for analysis was obtained through a partnership with OpenVibe (France), a neuroscience community based around “a software platform that enables the design, test, and use Brain-Computer Interfaces (BCIs).” This research group is dedicated to the proliferation of open source EEG information for use in research and laboratory environments. OpenVibe provides the opportunity to collect test data that can be used, in the case of this research, for computational neuroscience and signal processing. The main goal of OpenVibe is to provide data that can be used in the development of BCIs and numerical neurological algorithms.

The experimental data is comprised of fourteen total records of motor imagery where a subject was requested to imagine left or right hand motor movement with emphasis on movement of the thumb and forefinger [3]. This experiment was conducted using an 11-channel data collection method governed by the 10-20 EEG placement structure [8]. The following figure shows a 3D model of the 11-channel electrode array used in this experiment

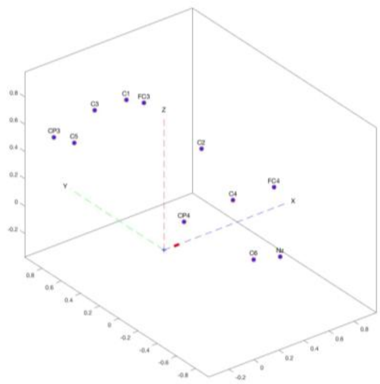

Fig.1. EEGLab 3D Electrode Channel Placement

These channels, shown above, are C3, C4, Nz, FC3, FC4, C5, C1, C2, C6, CP3, and CP4. Channel Nz can be used as reference and all channels were recorded in common average mode. The collected signal was sampled at 512Hz using the OpenVibe MindMedia Nexus32B bioinstrumentation amplifier. For each of the fourteen records (trials), a CSV file was generated showing the raw signal (in volts) of each sample.

Data was collected in an effort to discriminate between two mental states; one involving the imagination of left hand motor movement, the other the imagination of right hand motor movement based on a visual stimulus presented by a monitor. A monitor is placed 150cm in front of the subject. Upon beginning the experiment, a crosshair is displayed on the screen bisecting the screen in the vertical as well as horizontal orientation. At $t = 2000ms$ an auditory warning is played indicating the initiation of that individual trial. At $t = 3000ms$ an arrow pointing either left or right (randomized) is displayed on the screen for a total time of $\Delta t = 1250ms$ from $t = 3000ms$ to $t = 4250ms$[3]. During the presence of the arrow, the subject is asked to imagine the movement of their left or right hand with emphasis on the thumb and forefinger without actually performing the movement while corresponding to the orientation of the displayed arrow.

Upon collection of all data (40 trials of left and right randomized arrows for a total of fourteen patients) [3], the dataset is sorted into three files, one of which contains raw signal values (in microvolts) for each sample. One can then use a third party analytic tool such as Matlab to plot the data set. For each trial the data set takes on the following structure:

- 14 total subjects
- 40 trials per subject
- Each trial contains raw information from eleven channels (C3, C4, Nz, FC3, FC4, C5, C1, C2, C6, CP3, and CP4)
- Each of the 14 subjects information is collected at a sampling rate of 512 Hz
- Roughly 317824 samples from each electrode per subject

V. Data Import into EEGLab

The signal was analyzed, in part, using EEGLab, an interactive Matlab toolbox developed by the Swartz Center for Computational Neuroscience at the University of California San Diego [14][15]. This toolbox is focused around an interactive graphical user interface (GUI), which allows for the processing and plotting of high-density EEG data. In addition to providing a computational space for EEG signal processing, EEGLab also provides a series of tools that can be used for analysis of EEG data [15].

Initially, channel data was imported into the Matlab environment. As mentioned, each channel held 317824 samples collected over the course of the experiment. When imported into Matlab, each channel was imported as a 317824x1 double. Data from all eleven channels was collated into an 11x317824 double with channels in the order they appear in EEGLab. This data was initially imported into Matlab and plotted as shown in the following figure. It is important to note the relationship between the sampling frequency of 512 Hz, total time of $t = 620.748s$, and number of samples 317824.

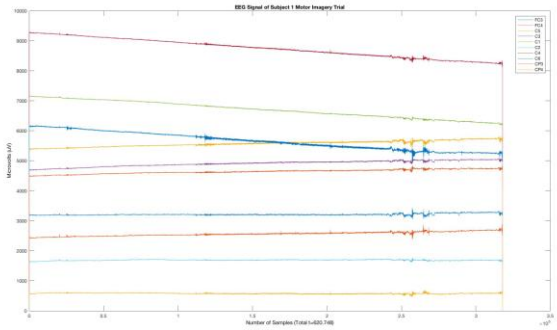

Fig.2. Matlab Signal Representation

After plotting the data in Matlab, the .mat file was imported into the EEGLab simulation ecosystem. The data was epoched into 62 ms intervals and plotted as a function of time. Additionally, known "bad" sections of data such as clear motion artifacts, which result in noisy sections of data from a translational shift in the skin/electrode interface, were rejected [8][10][16].

Furthermore, linear trends were rejected from the dataset [14]. It is advisable to filter the data before epoching or artifact removal. Filtering the data using a high pass filter minimizes the introduction of filtering artifacts at epoch boundaries. At various epochs, or time divisions of data, it is important to avoid filtering artifacts to retain the waveform fidelity for ERP extraction. A basic FIR filter, whose magnitude is shown theoretically in the following figure, was used. The lower edge frequency was set to 1 Hz. The following figure shows the magnitude response of a FIR high pass filter like the one used for signal preprocessing.

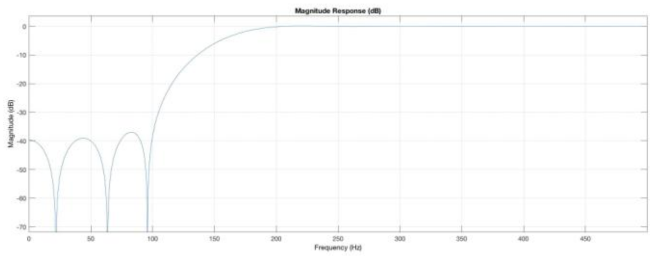

Fig.3. Low Pass Filter Magnitude Response

The following figure shows the data imported, filtered, epoched, and displayed in the EEGLab ecosystem.

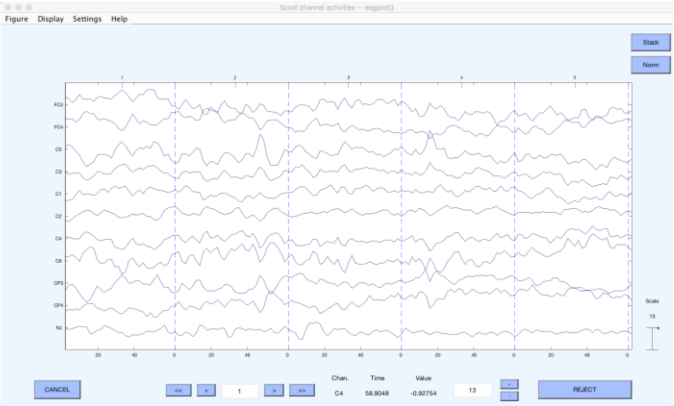

Fig.4. Channel Import into EEGLab

VI. Power Spectrum and Scalp Energy Distribution

After data was imported into the EEGLab environment, filtered, and preprocessed (as indicated in the previous section), known "bad" data was rejected by scrolling through the continuous data stream shown in Fig.4 and erasing problematic data. This made it possible to investigate the power spectra, also known as power spectral density (PSD) of the dataset being examined. Using the tools provided in the EEGLab simulation landscape, a series of frequencies were examined.

PSD for each channel was plotted as a function of a range of frequencies [9]. Each channel is represented as a colored line and the scalp power distribution is represented as a topological map for each frequency of interest [14].

These topological maps allow the user to establish an area of examination for further analysis. This is especially important because neurophysiological signals are complex in nature and an iterative approach must be taken to narrowing down frequencies (and locations) of interest. Initially, frequencies ranging from $1\,Hz$ to $24\,Hz$ were plotted. Upon further examination, temporal energy concentrations became less dense outside the frequencies of interest. The following figure illustrates the frequencies that were determined to be significant.

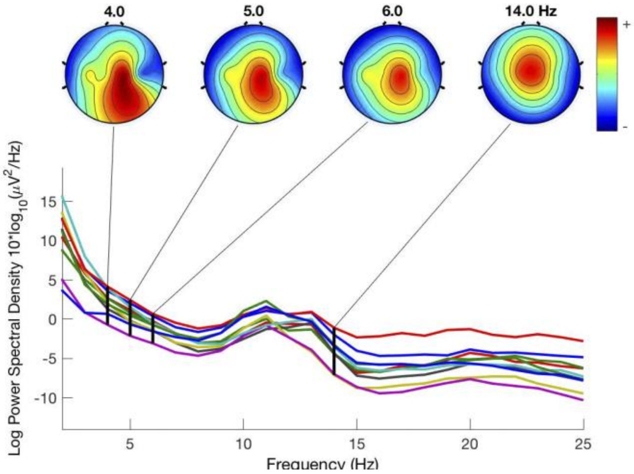

Fig.5. 2D Channel PSD and Scalp Power Distributions

From the above figure, it is evident (and expected) that power density varies at various frequencies. However, it was noticed that power distributions begins to show temporal resolution beginning around the $4\,Hz$ mark and remains consistent through approximately $6\,Hz$ where power distribution begins to drop off up until roughly $16\,Hz$ where the power distributions again begin to lose temporal resolution.

When examining the power spectrum in the range of $4\,Hz$ to $6\,Hz$ we notice high correlation between PSD and channels C4 and CP4. This provides resolution into the portion of the primary motor cortex responsible for the motor movement as described in the aforementioned experiment. This data is corroborated in a later section of this paper by plotting the spectrogram of each data channel.

VII. Formulation of ERPs and 3D Scalp Plots

After plotting the PSD, which allows the user to determine that data is ready for further analysis, the epoched data was investigated further. The data, captured over the course of $620.748\,s$ at a rate of $512\,Hz$, resulted in 317824 samples. The epoch time for the dataset was $62.5\,ms$ with 32 time events occurring for every epoch. As a result, the dataset, which spanned the course of 620.748s, was broken into 9932 separate epochs.

These time locked trial averages are known as event related potentials, or ERPs [3][8][9][14]. These ERPs, representing significant events, were extracted and plotted on a two-dimensional topological map corresponding to the 11 channels used during the course of the experiment [8][12].

Since one epoch has a time span of $62.5\,ms$ and the dataset spanned $620.748\,s$, ERPs of interest across the dataset were averaged into one singular average ERP per channel. In the following figure, each line represents the averaged ERP calculated for each channel. For the range of $t = 0ms$ (the start of the average ERP) to $t = 62.5ms$ a three-dimensional scalp map was plotted to investigate the power distribution of each electrode over the course of the ERP's latency [15][16].

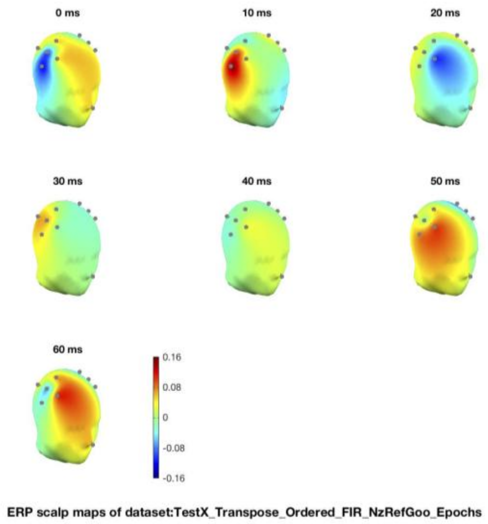

Fig.6. 3D Average ERP PSD and Scalp Power Distributions

It is important to note that around the $10ms$ latency, significant power distributions are seen around the C4 electrode. It is important to note that the electrode placements are not exact since discrepancies between actual skull dimensions and that of skull dimension within the simulation may vary [18]. These data plots provide a power distribution, which narrows the area of observation that is supported by finer STFT analysis in the following section

VIII. Channel Spectrogram

From the results gathered using the EEGLab simulation, spectrograms could be generated for each recording channel in the dataset. As mentioned previously, the spectrogram is a two dimensional visualization which shows data correlating the observed frequencies with the times at which they occur [1]. Elevation of energy was seen in electrodes C4 and CP4 when compared to less activated electrodes such as that of electrode C1, which showed significantly less activation.

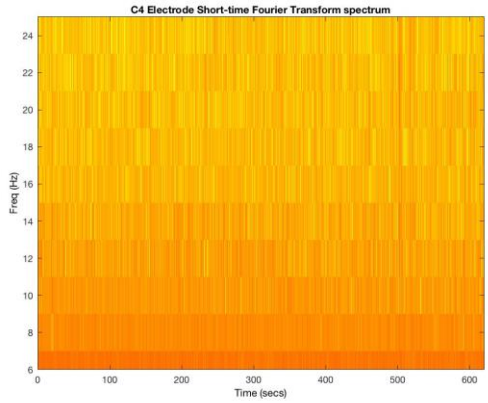

Fig.7. Electrode C4 Spectrogram

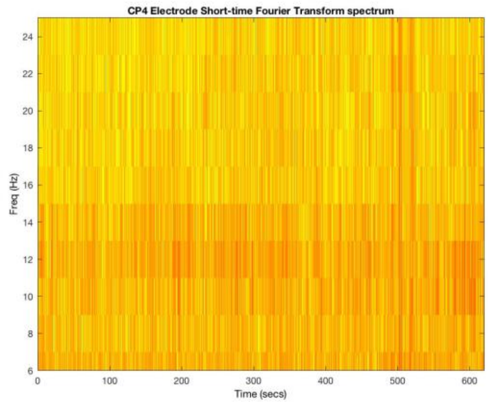

Fig.8. Electrode CP4 Spectrogram

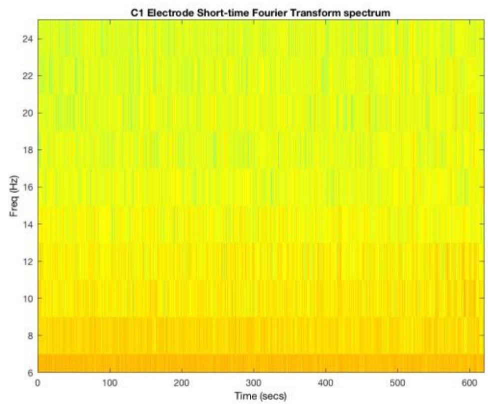

Fig.9. Electrode C1 Spectrogram

It is also important to note that frequency distributions in the above spectrograms begin to gradually fall off at approximately 14 Hz, the mark at which sinusoidal temporal frequencies begin losing resolution when investigating the PSD using EEGLab as seen in the following figure

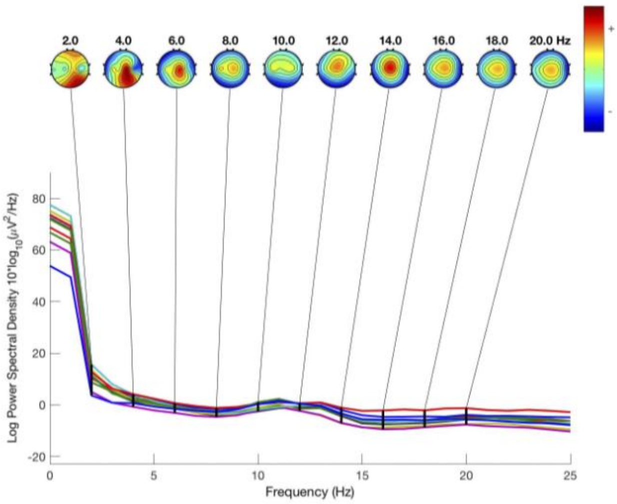

Fig.10. 2D Channel PSD and Scalp Power Distributions for Investigated Frequency Range

IX. Conclusion

In conclusion, a significant correlation between imagined motor movement, with emphasis on the thumb and forefinger, and localization within the brain was found using the Hanning-based Short Time Fourier Transform. Accompanying numerical analysis tools such as the FIR filtering, power spectral density, and the spectrogram were able to corroborate these results. By conducting this analysis on test data collected on live subjects through partnership with OpenVibe, a significant correlation between EEG channels C4 and CP4 and power distributions could be established. This proves a significant link between the use of the STFT and localization of motor movement within the human brain.

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