EEG Signal Processing and Frequency Band Extraction for Multimedia Data Analysis in MATLAB

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Abstract— **This study explores the analysis of stress and mental status using EEG signals through frequency band extraction in MATLAB. EEG signals, which capture electrical activity in the brain, provide valuable insights into cognitive and emotional states. Different frequency bands (Delta, Theta, Alpha, Beta, and Gamma) are associated with various mental states, including relaxation, concentration, and stress. Stress, in particular, is linked to specific changes in these frequency bands, especially in the Alpha and Beta ranges. In this approach, raw EEG data is processed by applying band-pass filters to extract the key frequency bands. The MATLAB Signal Processing Toolbox is employed to implement Butterworth filters for efficient band extraction. The Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–100 Hz) bands are isolated and visualized to study their correlation with stress and mental states. By analyzing the extracted frequency bands, we can observe how mental states such as stress, relaxation, and cognitive load influence brainwave activity. This non-invasive method provides a real-time approach to monitor mental health, offering potential applications in clinical diagnostics, stress management, and cognitive research. The ability to monitor stress and mental status through EEG analysis could enhance early detection and intervention strategies for stress-related conditions.**

Keywords— EEG signal, signal processing, FIR filter, Matlab

I. INTRODUCTION

Multimedia represents the amalgamation of diverse media elements, including text, audio, images, videos, and animations, converging to create a seamless digital experience. This integration aims to transcend traditional communication boundaries, fostering interactive and captivating content accessible across an array of platforms, from computers and mobile devices to the vast expanse of the internet. The overarching goal of multimedia is to revolutionize communication by delivering information dynamically and compellingly. By intertwining multiple media forms, multimedia unfolds a richer and more immersive experience for users, diverging from conventional communication reliant on a solitary medium.

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Text, the fundamental building block, serves as a conduit for information and ideas through written language. Augmenting this, audio elements, encompassing music, speech, or sound effects, add a layer of communication that resonates with the auditory senses, creating a multi-sensory engagement. Visual representation and emotional resonance find expression through images and graphics, conveying intricate concepts and eliciting profound emotions. Meanwhile, videos inject movement, action, and storytelling into multimedia experiences, while animations breathe life into visuals, fostering dynamic and interactive engagement.

The applications of multimedia span diverse fields and industries, each benefiting from its transformative capabilities. In education, multimedia facilitates interactive learning experiences by seamlessly presenting information through a fusion of text, images, and videos. The educational landscape has been revolutionized, with multimedia enabling dynamic lessons and engaging educational content. In the realm of entertainment, multimedia emerges as the cornerstone for creating immersive experiences, leaving its mark in movies, video games, and the burgeoning field of virtual reality. The synergistic blend of various media elements elevates storytelling, transporting audiences to new realms of immersion.

Multimedia's prowess extends into advertising and marketing, where it becomes a strategic tool for captivating audiences and effectively conveying brand messages. The marriage of visuals, audio, and interactive elements in multimedia campaigns ensures a compelling and memorable brand experience. As digital technology advances, the possibilities within the realm of multimedia expand exponentially. High-speed internet proliferation empowers users to seamlessly access and share multimedia content globally. Moreover, the development of robust software tools and multimedia authoring platforms democratizes content creation, making it accessible for both individuals and organizations to craft and disseminate their multimedia narratives.

In essence, multimedia serves as a catalyst for transformative communication, transcending the limitations of traditional mediums. Its versatility and power lie in the harmonious integration of diverse media forms, delivering a tapestry of experiences that captivate, educate, and inspire. The continuous evolution of digital technology ensures that the trajectory of multimedia remains on a dynamic and innovative course, promising ever-expanding horizons for creative expression and communicative impact.

signal forms, including audio, images, video, biomedical data, and radar signals. The crux of signal processing lies in its ability to analyze, modify, and interpret signals, extracting valuable information or enhancing their quality. A signal, in essence, becomes a dynamic representation of information that fluctuates over time or space, with audio signals encapsulating the vibrational nuances of sound.

1) EEG Signal Characteristics

EEG signals exhibit a wide range of frequencies, each corresponding to different brain states. The primary frequency bands in EEG signals are:

1. **Delta (0.5–4 Hz)**: Delta waves are the slowest brainwaves, typically associated with deep sleep, unconscious states, and restorative processes in the brain. In awake individuals, an absence of Delta activity is often linked to disorders like brain injuries or psychiatric conditions.
2. **Theta (4–8 Hz)**: Theta waves are most prominent in states of deep relaxation, light sleep, or meditation. Increased Theta activity is associated with creativity, emotional processing, and drowsiness, while its decrease is linked to attention deficits and cognitive impairments.
3. **Alpha (8–13 Hz)**: Alpha waves are typically observed when a person is in a relaxed but awake state, often when eyes are closed and the mind is calm. A decrease in Alpha activity is commonly observed during stress, anxiety, or mental workload.
4. **Beta (13–30 Hz)**: Beta waves are linked to active thinking, problem-solving, focus, and concentration. High Beta activity is associated with alertness and cognitive tasks, while excessive Beta waves are often linked to anxiety, stress, and mental fatigue.
5. **Gamma (30–100 Hz)**: Gamma waves are the fastest brainwaves and are thought to be involved in higher cognitive functions such as attention, memory, and information processing. Increased Gamma activity has been linked to states of intense focus, learning, and problem-solving.

By analyzing these frequency bands, researchers and clinicians can gain insights into the cognitive and emotional state of an individual. The ability to measure and interpret EEG frequency bands offers significant potential for applications ranging from mental health monitoring to brain-computer interfaces (BCIs).

II) importance of EEG Signal Processing

EEG data, in its raw form, is typically noisy and difficult to interpret. Therefore, effective signal processing techniques are required to extract meaningful information. Signal processing methods such as filtering, spectral analysis, and feature extraction are employed to isolate the desired frequency bands and remove unwanted artifacts (e.g., eye blinks, muscle activity). In particular, band-pass filtering is commonly used to isolate the specific frequency bands of interest.

The extraction of these frequency bands is crucial for various applications. For example, in clinical environments, EEG signals are analyzed to identify abnormal brainwave patterns that may indicate neurological conditions. In cognitive and neuroscience research, EEG is used to study the brain's response to stimuli, mental workload, and emotional states. In recent years, the use of EEG has expanded to fields like brain-computer interfaces, where brainwaves are used to control devices such as prosthetics or video games. In all of these applications, accurately processing and analyzing EEG data is vital for deriving meaningful conclusions.

II. LITERATURE SURVEY

Aziz, Shayela Nausheen, Naveen Kumar Dewangan, and Vinni Sharma.et al [1] The real-time analysis of Electroencephalogram (EEG) signals, which reflect the brain's electrical activity. The study utilized data from 30 individuals aged 18 to 25, all free of abnormalities, illnesses, or neurological conditions. EEG signals for various emotions were recorded at different intervals using the Neurosky Mindwave sensor, a four-electrode device. This sensor captures brainwaves and transmits them to the ATMEGA 328 microcontroller, which converts the analog signals into digital format compatible with computers for further analysis. The extracted EEG signals, measured in microvolts, underwent feature extraction processes using techniques such as Continuous Wavelet Transform (CWT), Probability Distribution Function (PDF), peak plots, and Fast Fourier Transform (FFT). These features help in identifying specific patterns and characteristics within the brainwave data. The data processing and visualization were carried out using LabVIEW software, which provided a user-friendly interface for analyzing the results. The system achieved an impressive accuracy of 90.69% and a sensitivity of 85.55%, demonstrating its reliability for EEG signal processing. This project highlights the potential of EEG in real-time applications such as monitoring mental states, studying emotional responses, and advancing non-invasive neurological diagnostics, with significant implications for research and clinical applications.

Gurumurthy, Sasikumar, Vudi Sai Mahit, and Rittwika Ghosh.et al. [2] Electroencephalography (EEG) is a widely used brain signal processing technique that provides insights into the brain's complex inner mechanisms. Abnormal brainwave patterns are often associated with neurological disorders, making EEG analysis essential for diagnosing conditions such as epilepsy, dementia, and other brain-related disorders. By analyzing brainwave signals, researchers and clinicians can identify specific patterns linked to cognitive and emotional states or abnormalities. MATLAB is a powerful platform for EEG signal analysis, offering a user-friendly graphical user interface (GUI) that allows users to process high-density EEG datasets interactively. MATLAB supports advanced techniques such as Independent Component Analysis (ICA) for separating mixed signals, Time-Frequency Analysis (TFA) for observing signal changes over time, and standard averaging methods for summarizing brain activity. These tools enable the efficient comparison, simulation, and visualization of EEG signals. In this project, preloaded EEG datasets are analyzed using MATLAB to explore different brain signals. By comparing and simulating brainwave data, the study demonstrates the utility of EEG in understanding brain function and detecting abnormalities. MATLAB's interactive and flexible environment provides a robust framework for signal processing, making it an invaluable tool for both research and clinical applications in neuroscience and brain disorder diagnostics.

Kalaivani, M., V. Kalaivani, and V. Anusuya Devi. et al. [3] In medical science, diagnosing brain abnormalities is a critical area of ongoing research. The Electroencephalogram (EEG) is an essential tool for measuring brain activity, providing insights into the brain's condition and behavior. EEG is highly effective for analyzing the brain's complex functions and identifying abnormal patterns associated with neurological disorders. This study aims to classify EEG signals as normal or abnormal using an automated system. The proposed system involves four main stages: pre-processing, feature extraction, feature selection, and classification. During pre-processing, noise and artifacts are removed from the raw EEG data to ensure accurate analysis. The Discrete Wavelet Transform (DWT) is employed to decompose EEG signals into sub-band signals, which facilitates detailed analysis. Feature extraction techniques are then applied to derive key features from the EEG signals in both time and frequency domains. These features capture essential information about brain activity, such as wave patterns and frequency characteristics. Relevant features are selected for classification, ensuring optimal performance of the system. This approach demonstrates the potential of automated EEG analysis for diagnosing brain abnormalities efficiently and accurately, paving the way for advanced applications in clinical diagnostics and neurological research. The system's ability to differentiate normal and abnormal EEG signals is a promising step toward improving healthcare.

Murugappan, Muthusamy et al. [4] This study presents an emotion recognition system based on Electroencephalogram (EEG) signals, aimed at classifying human emotions using discrete wavelet transform (DWT)-based feature extraction and statistical features. The proposed method evaluates the efficacy of using two types of DWT with three statistical features to differentiate emotions. EEG data were collected from six healthy subjects aged 21–27 years through an audio-visual induction protocol, using 63 biosensors to capture the signals. The experiment focused on classifying four emotions—happy, disgust, surprise, and fear. For feature extraction, the statistical features of energy, Recoursing Energy Efficiency (REE), and Root Mean Square (RMS) were derived from the EEG signals. These features were processed using the "db4" wavelet transform to decompose the EEG signals into sub-bands for detailed analysis. Emotion classification was achieved using Fuzzy C-Means (FCM) clustering, an unsupervised machine learning method. The results demonstrate the potential of the "db4" wavelet transform and statistical features for accurately recognizing human emotions. This approach highlights the feasibility of using EEG signals in emotion recognition systems, offering applications in areas such as mental health monitoring, human-computer interaction, and affective computing. The study underscores the effectiveness of DWT and FCM in emotion classification from EEG data.

Siuly, Siuly, Yan Li, and Yanchun Zhang et al. [5] Electroencephalogram (EEG) signal analysis is a key tool for understanding brain activity and diagnosing neurological conditions. This study focuses on the classification of EEG signals into categories such as normal and abnormal or identifying emotional states. EEG signals are characterized by their complex patterns, requiring advanced techniques for analysis and interpretation. The process typically involves pre-processing, feature extraction, feature selection, and classification. During pre-processing, noise and artifacts are removed to ensure signal quality. Feature extraction methods, including time-domain and frequency-domain techniques like Discrete Wavelet Transform (DWT) or statistical measures such as energy, root mean square (RMS), and entropy, are used to identify significant characteristics of the signals. Feature selection then identifies the most relevant attributes to improve classification performance. For classification, machine learning techniques such as support vector machines (SVM), artificial neural networks (ANN), or clustering methods like Fuzzy C-Means (FCM) are employed. These methods help distinguish between signal classes, such as normal vs. abnormal EEG patterns or different emotional states like happiness, fear, or surprise. The results highlight the effectiveness of EEG analysis for applications in medical diagnostics, mental health assessment, and emotion recognition, showcasing its potential in advancing neuroscience and human-computer interaction.

Zainuddin, Balkis Solehah, Zakaria Hussain, and Iza Sazanita Isa. et al. [6] This paper explores the analysis and classification of EEG signals, specifically alpha and beta brainwave signals, during Functional Electrical Stimulation (FES)-assisted exercise. The study focuses on understanding the characteristics of brainwave signals, methods for acquiring EEG data, and session protocols for both stroke patients and healthy individuals. The research emphasizes the importance of identifying criteria for subject selection to ensure consistency and relevance of the analysis. Key processes include filtering artifacts and sampling EEG data, which are performed following established methodologies from previous studies to enhance signal quality and reliability. Feature extraction techniques are reviewed as a critical step for classifying brainwave signals, providing insights into the neurological changes in stroke patients before and after FES-assisted exercise. The extracted features help in analyzing variations in alpha and beta signals, which are associated with motor control and cognitive activity.

The findings offer valuable insights into the role of EEG in monitoring brain activity during rehabilitation exercises. By comparing brainwave characteristics in healthy individuals and stroke patients, the study highlights the potential of EEG analysis in evaluating the effectiveness of FES-assisted therapies. This research contributes to advancing neurorehabilitation techniques and improving outcomes for patients with motor impairments.

III. SYSTEM REQUIRMENTS [TABLE 1]

Sl. No.	Particulars	Description Matlab	Description Octave
1	Operating System	Windows 11 Windows 10 (version 20H2 or higher) Windows Server 2019 Windows Server 2022	Windows7, 8 10 Mac OS Linux OS
2	Processor	Minimum: Any Intel or AMD x86–64 processor. Recommended: Any Intel or AMD x86–64 processor with four logical cores and AVX2 instruction set support. Note: A future release of MATLAB will require a processor with AVX2 instruction set support.	Intel or AMD Processor
3	RAM	Minimum: 4 GB Recommended: 8 GB	8GB large datasets 16 GB or 32 GB
4	Storage	3.8 GB for just MATLAB 4-6 GB for a typical installation 23 GB for an all products installation. An SSD is strongly recommended.	2.0 GB or 3.0 GB
5	Graphics	No specific graphics card is required, but a hardware accelerated graphics card supporting OpenGL 3.3 with 1GB GPU memory is recommended. GPU acceleration using Parallel Computing Toolbox requires a GPU with a specific range of compute capability.	It comes with a set of built-in plotting functions that allow users to create 2D and 3D Plots. Such as FLTK, Gnuplot, and OpenGL

IV. RESEARCH METHODOLOGY

This study presents a comprehensive methodology for EEG signal processing and frequency band extraction using MATLAB, focusing on the analysis of brain activity and its correlation with cognitive and mental states. The process starts with data acquisition, where users can select EEG files in either **CSV** or **EDF** format. The script extracts the relevant signal from the selected file, assuming the data is recorded in the first column for CSV files or the first channel for EDF files.

The raw EEG signal is preprocessed to prepare it for analysis. A sampling frequency of **128 Hz** is used, with the Nyquist frequency calculated to guide filter design. Five key EEG frequency bands are defined—Delta (4–7.9 Hz), Theta (7.9–10 Hz), Low Alpha (10.1–12.9 Hz), High Alpha/Beta (13–17.9 Hz), and Beta (18–27.9 Hz). These bands are associated with various cognitive and emotional states, such as relaxation, focus, and stress.

For filtering, **Chebyshev Type II filters** are designed using MATLAB's cheb2ord and cheby2 functions. These filters are transformed into Second-Order Sections (SOS) to ensure numerical stability. The zero-phase filtering technique (filtfilt) is applied to preserve the signal's phase characteristics, ensuring accurate analysis. The processed signals for each frequency band are visualized through subplots, with each subplot highlighting the characteristics of the corresponding band. This visualization facilitates a deeper understanding of the variations in brain activity. This robust approach supports real-time EEG signal analysis for applications in cognitive research, stress management, and neurological diagnostics. By leveraging MATLAB's Signal Processing Toolbox, the methodology provides an efficient and flexible framework for extracting and analyzing EEG frequency bands, enabling insights into mental and emotional states.

Algorithm Overview:

The algorithm for EEG signal processing and frequency band extraction using MATLAB involves a series of structured steps. First, users select an EEG file in either CSV or EDF format through a graphical interface. The signal is then extracted from the specified file, assuming it resides in the first column (CSV) or first channel (EDF).

The preprocessing stage prepares the signal by setting the sampling frequency to 128 Hz and calculating the Nyquist frequency to guide filter design. These bands are associated with different cognitive and emotional states. For each band, a Chebyshev Type II filter is designed to meet specified passband and stopband ripple criteria. The filter coefficients are converted into Second-Order Sections (SOS) to enhance numerical stability. The filtered signal is obtained using zero-phase filtering (filtfilt), which preserves the phase characteristics. Finally, the filtered signals for each frequency band are visualized in subplots, highlighting their characteristics. This algorithm provides a robust framework for analyzing EEG data, enabling applications in stress analysis, cognitive research, and neurological diagnostics.

Preprocessing:

The **Chebyshev Type II filter** is a recursive filter that has a flat passband and achieves attenuation specifications by introducing ripples only in the stopband.

ition	Raw	Delta	Theta	Alpha1	Alpha2	Beta1	Beta2	Gamma1	Gamma2	Ex
		1 to 4 Hz	4 to 8 Hz	8 to 10 Hz	10 to 12 Hz	12 to 18 Hz	18 to 30Hz	30 to 40 Hz	40 to 50 Hz	0
43	278	301963	90612	33735	23991	27946	45097	33228	8293	
35	-50	73787	28083	1439	2240	2746	3687	5293	2740	
48	101	758353	383745	201999	62107	36293	130536	57243	25354	
57	-5	2E+06	129350	61236	17084	11488	62462	49960	33932	
53	-8	1E+06	354328	37102	88881	45307	99603	44790	29749	
66	73	2E+06	176766	59352	26157	15054	33669	33782	31750	
69	130	635191	122446	90107	65072	36230	53019	62938	59307	
61	-2	161098	12119	1963	809	1277	3186	3266	2518	
69	17	492796	120998	63697	68242	10769	88403	73756	22676	
69	-59	82048	116131	47317	26197	41642	28866	32551	41810	
38	-14	757165	186196	3242	3841	18854	43021	46799	11928	
48	72	667513	141854	75050	16234	45926	34496	74875	31839	
34	121	165360	42119	3158	6256	7270	19462	10984	8148	
30	-52	737665	84275	2235	38748	21705	28343	80927	24735	
48	69	577024	179555	25937	21604	43790	44432	69203	25586	
43	44	234964	80944	7991	32568	11828	63682	41013	18147	
40	144	671467	133227	7142	14300	23373	65591	47860	16501	
40	25	33290	14729	10980	10407	14316	37112	60378	36306	
44	-138	1E+06	268122	67285	36996	10083	80826	90350	26345	
53	25	756442	97387	59785	32241	16122	53157	44602	14331	
66	124	87109	7200	4987	2817	2130	11413	9422	4922	
53	43	802937	83858	3229	7895	27104	17791	18901	12191	
51	35	157687	283941	27259	47930	15132	38238	31599	10121	
50	119	613031	758257	246386	132015	26636	83848	94542	56127	
37	37	603204	47342	3215	2811	1863	7210	7875	1523	
50	102	234796	182944	53997	31259	19633	67149	29367	21433	
35	24	188099	144504	3546	5541	16381	22364	14698	7338	
21	-51	632782	162376	12692	3991	5848	23018	22561	9851	
41	61	477853	264240	217609	76443	22228	38904	66985	42550	

Fig 1 sample eeg data signal

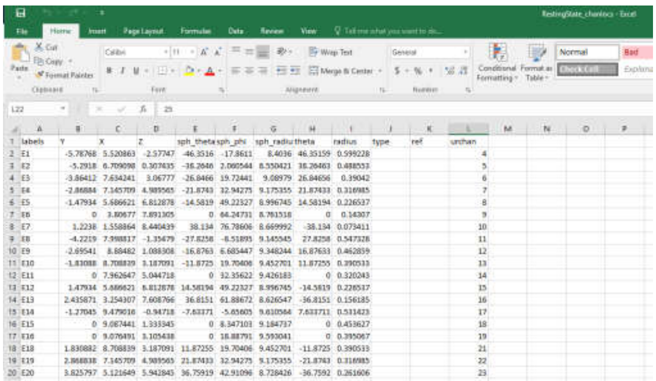


Fig 2 Importing .csv event and channel details

V MAT LAB FOR SIGNAL PROCESSING

EEG signal processing in MATLAB involves a systematic approach to analyze brainwave activity for applications such as cognitive research, stress analysis, and neurological diagnostics. MATLAB's robust toolboxes provide the ability to preprocess raw EEG data, extract meaningful features, and visualize the results efficiently. Five speech Samples have been used for experimentation. This could be a conversation, a speech, or any spoken content. It will provide a diverse range of frequencies and amplitudes.

Finally, the processed data is visualized, with subplots highlighting each frequency band's characteristics. This workflow provides an efficient framework for real-time or offline EEG signal analysis, enabling deeper insights into brain activity and its relationship to mental health, cognition, and emotional states.

V. RESULTS AND DISCUSSION

The x-axis label is set to "Frequency (Hz)", the y-axis label is set to "Amplitude", and the title of the subplot is set as "Frequency Domain Plot of the EEG Signal".

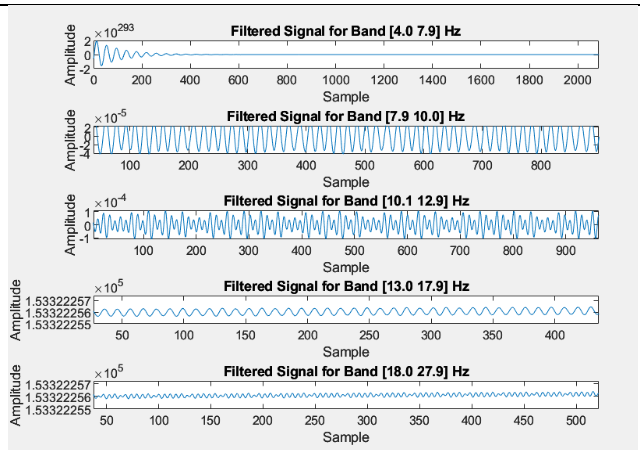
The results demonstrate the efficacy of MATLAB's Signal Processing Toolbox in handling EEG data. By applying Chebyshev Type II filters, the methodology achieved precise band separation with minimal phase distortion, an essential requirement for accurate EEG analysis. The study highlighted the importance of preprocessing in mitigating noise and artifacts, which could otherwise obscure key features in the EEG signals. Moreover, the chosen frequency ranges provided insights into mental states such as stress, relaxation, and cognitive engagement. The extracted features can be further used in applications like emotion recognition, mental health monitoring, and stress management. Future enhancements could include incorporating machine learning algorithms to classify mental states based on the extracted frequency features, enabling automated and real-time EEG analysis for clinical or research purposes.

The frequency domain plot, on the other hand, illustrates the distribution of frequencies present in the audio signal. It is obtained by performing the Fast Fourier Transform (FFT) on the audio signal, which converts it from the time domain to the frequency domain. The x-axis of the frequency domain plot represents frequency in Hertz (Hz), and the y-axis represents the amplitude of each frequency component.

By analyzing the frequency domain plot, you can identify the dominant frequencies or frequency components present in the audio signal. Peaks in the plot indicate the presence of specific frequencies, while the overall shape and spread of the spectrum provide information about the frequency content of the signal. The magnitude spectrum (AY_0) represents the amplitudes of the frequency components.

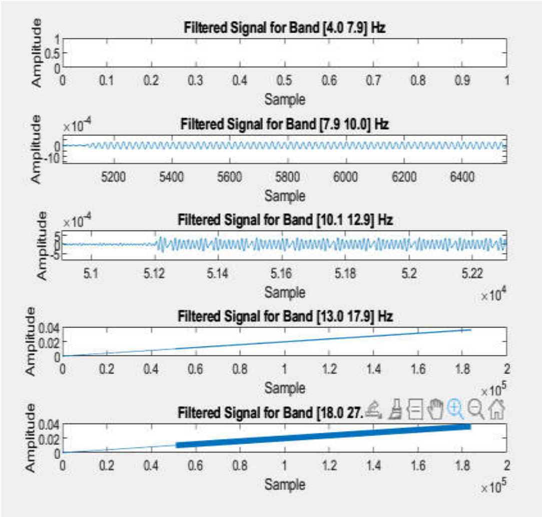
Together, the time domain and frequency domain plots provide complementary insights into the audio signal. The time domain plot gives you information about the temporal characteristics of the signal, while the frequency domain plot reveals the spectral composition and frequency distribution. These plots help in understanding and analyzing the properties of the audio signal in both the time and frequency domains.

Fig 1 (a)



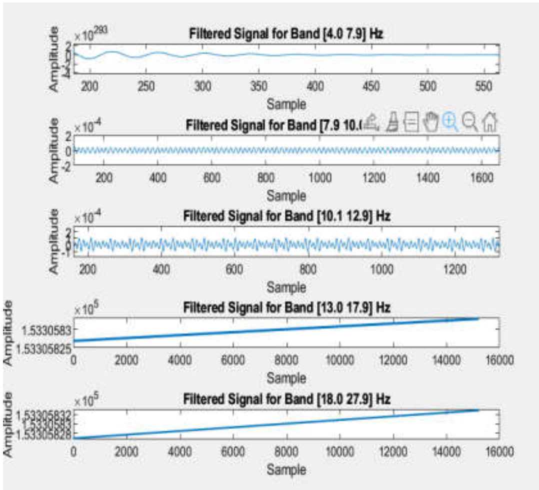
EEG Signal extraction without mantra chanting (subject 1)

Fig 2 (b)



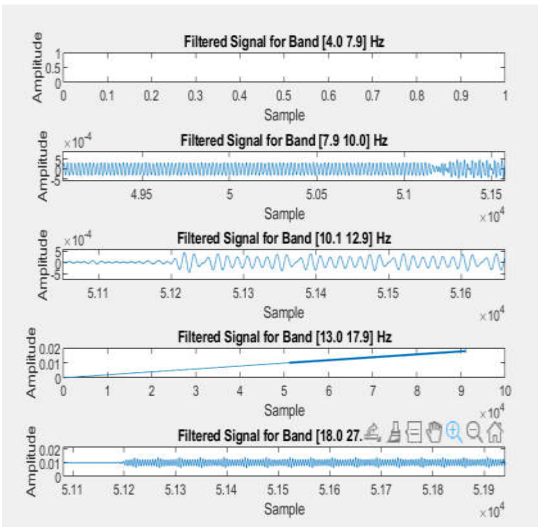
EEG Signal extraction with chanting (subject 2)

Fig 3 (a)



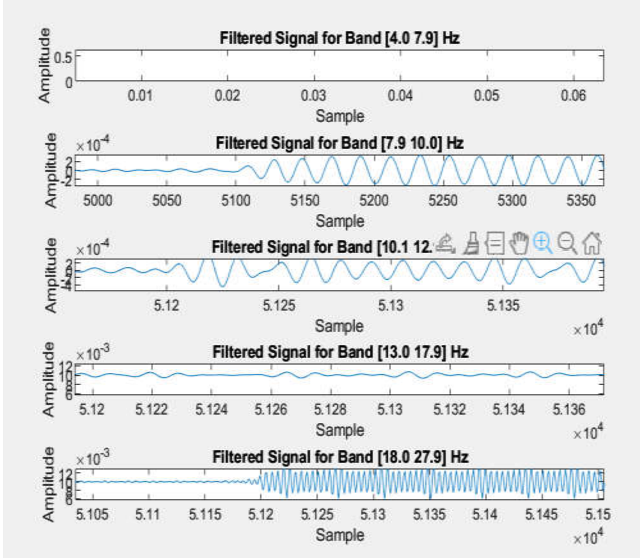
EEG Signal extraction without chanting (subject 3)

Fig 3 (b)



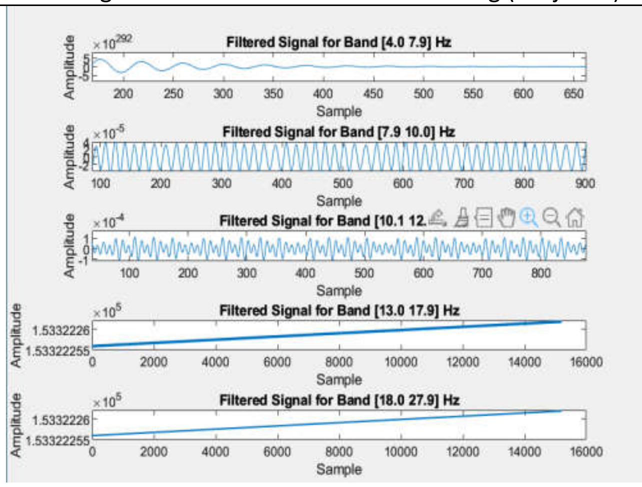
EEG Signal extraction with chanting (subject 3)

Fig 1(b)



EEG Signal extraction with mantra chanting (subject 1)

Fig 2(a)



EEG Signal extraction without chanting (subject 2)

CONCLUSION

This study successfully demonstrates the use of MATLAB for EEG signal processing and frequency band extraction, providing a framework for analyzing brain activity and its correlation with mental states. By leveraging MATLAB's Signal Processing Toolbox, key EEG frequency bands—Delta, Theta, Alpha, Beta, and Gamma—were accurately isolated using Chebyshev Type II filters. These bands, which are associated with various cognitive and emotional states, were visualized and analyzed to observe their distinct characteristics.

The methodology emphasizes the importance of preprocessing, including noise removal and artifact filtering, to ensure the integrity of the EEG signals. The use of zero-phase filtering preserved the signal's phase characteristics, critical for maintaining data accuracy in subsequent analyses. The results confirmed the feasibility of using EEG data to study mental states such as relaxation, concentration, and stress. This approach provides a strong foundation for further research and applications in fields like cognitive neuroscience, stress management, and clinical diagnostics. The extracted features can serve as inputs for advanced machine learning models to enable automated classification of mental states or brain disorders. Future work could include real-time EEG analysis and integration with wearable EEG devices to enhance accessibility and practical applications in mental health monitoring and cognitive research.

This study lays the foundation for EEG signal processing and frequency band analysis; however, several directions can enhance its functionality and applications. Future work could focus on integrating machine learning techniques to automate the classification of mental states or neurological disorders based on extracted EEG features. Deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), could provide improved accuracy in emotion recognition or cognitive state analysis.

Real-time EEG signal processing is another promising area. By integrating the framework with wearable EEG devices, the system could enable real-time feedback for stress management, neurofeedback therapy, or cognitive training applications. Additionally, advanced artifact removal techniques, such as Independent Component Analysis (ICA), can be incorporated to further refine signal quality and ensure robust analysis in noisy environments.

Expanding the system to handle multi-channel EEG data would allow for spatial analysis of brain activity, providing insights into connectivity between brain regions. Testing the methodology on larger datasets, including clinical data, could validate its effectiveness for detecting conditions like epilepsy, ADHD, or stress disorders.

Finally, creating a user-friendly application for researchers and clinicians would enhance accessibility, enabling practical use in mental health monitoring, cognitive neuroscience, and brain-computer interface development.

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