ToMCAT Offline Viz

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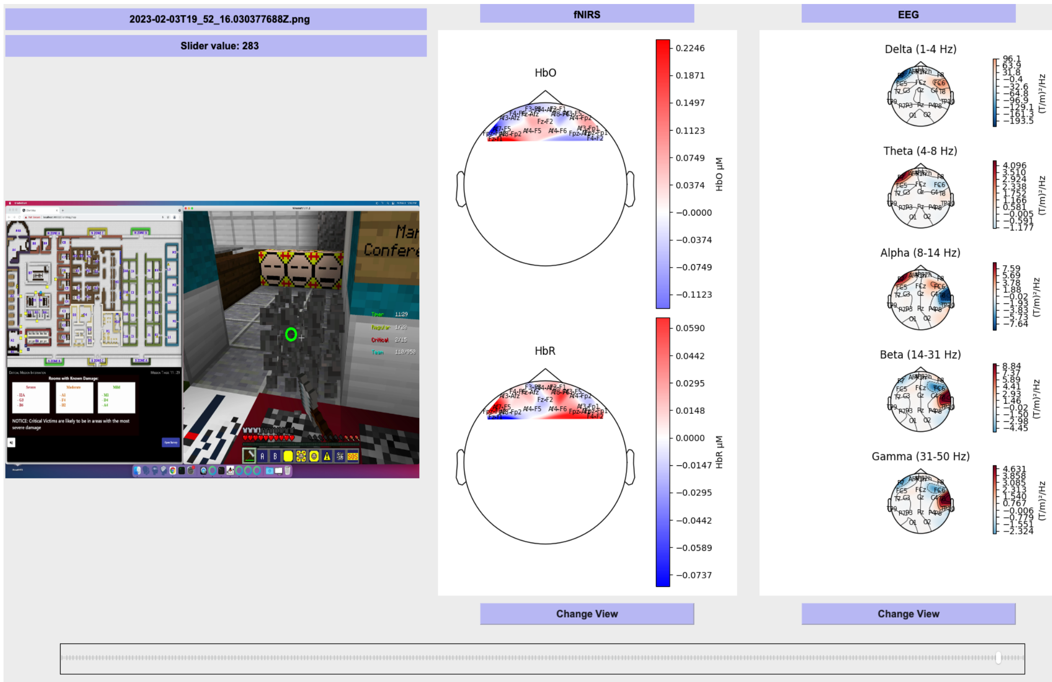

Fig. 1: Tomcat Offline Viz tool with Topological views for fNIRS and EEG signals. The green circle on the screenshot denotes the eye position at a given timestamp *(2023-02-03T19_52_16.030377688Z)*. The middle section shows a topological view of fNIRS *(HbO-oxyhemoglobin and HbR-deoxyhemoglobin)* data for 20 channels. On the right-most section, a topological view of EEG data is presented, which is categorized into different frequency bands, namely *Delta, Theta, Alpha, Beta, and Gamma*

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Abstract— ToMCAT (*Theory of Mind-based Cognitive Architecture for Teams*) offline viz tool is a collaborative project to develop an all-in-one multimodal (fNIRS, Eye tracker, EEG) visualization tool. To achieve this goal, the project accepts experimental data in the form of CSV files and screenshots (PNG) and visualizes this data to the users in a way that is easy to understand and analyze. The tool utilizes multiple modes of data, including functional near-infrared spectroscopy (fNIRS), eye tracking, and electroencephalography (EEG), to provide a complete picture of the cognitive and perceptual processes, such as attention, working memory, and emotion. By using this tool, researchers can gain valuable insights into how team members interact with each other through varying tasks and environments. The tool presents the data in a visually intuitive manner, by superimposing screenshots with eye-tracking data on the left and fNIRS/EEG data on the right that includes both signal and topological view. The ToMCAT Offline Viz tool is a valuable resource for social and computer scientists who are working on the ToMCAT project. It helps the users to read and analyze multimodal data in a way that is both efficient and informative, and to use this data to design an AI agent that can facilitate team coordination and global team optimization.

1 Introduction

The study of cognitive and neural mechanisms underlying teamwork is an essential field of research that has been gaining increased attention in recent years. However, understanding these complex mechanisms requires the use of sophisticated visualization tools that combine multiple modalities. To address this issue, our team is developing a new visualization tool called "*ToMCAT Offline Viz*," which can analyze eye-tracking, fNIRS, and EEG data simultaneously to gain a comprehensive understanding of team dynamics.

By superimposing eye-tracking data onto screenshots and displaying fNIRS and EEG data on the right-hand side of the screen, researchers can gain insights into the visual attention of team members and their neural activity. The tool also provides both signal and topological views of the fNIRS and EEG data, together with a slider that is utilized to compare continuous changes in each modality. This information is particularly valuable to social scientists who study the variation of signal waves as the subject's gaze shifts across different areas of a screenshot.

The visualization tool developed in this research paper provides users with the option to view both signal and topological representations of fNIRS and EEG data. Users can easily switch between these views by clicking a button, depending on their preference. To assist with the

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analysis of variations in the data, a slider is incorporated into the tool, allowing for a comparison of the continuous changes in each modality.

Furthermore, the slider is synchronized with the timestamps of each task and physiological data, as shown in Fig. 2. This feature enables users to pinpoint specific points in time and gain a better understanding of how neural activity and visual attention vary throughout the duration of the task. The use of such a tool can enhance the visualization and analysis of complex data, facilitating the identification of patterns and insights that might otherwise be overlooked.

The objective of our research is to tackle the issue of inadequate and non-user-friendly visualization tools for researchers studying cognitive and neural mechanisms. This problem is crucial as it has a direct impact on the ability of social and computer scientists working on the ToMCAT project to comprehend how individuals interact within teams. The development of efficient visualization tools is essential as it empowers researchers to gain a more profound understanding of the cognitive and neural mechanisms involved in effective team coordination.

Our innovative visualization tool has significant implications for the development of effective AI agents for team coordination and global team optimization. Overall, the development of the "*ToMCAT Offline Viz*" tool has the potential to make a valuable contribution to the field of cognitive and neural mechanisms of teamwork.

2 Background

2.1 About ToMCAT

To enhance the collaborative capabilities of AI agents in team settings, **Theory of Mind-based Cognitive Architecture for Teams (ToMCAT) [18]** project proposes an integrated approach that encompasses all critical abilities. These abilities include accurately deducing the internal states of other agents, collaborative problem-solving, and socially aware communication. ToMCAT's primary objective is to create an AI agent that can effectively facilitate collaboration by focusing on a specific set of essential abilities and seamlessly integrating them into a unified framework.

ToMCAT [18] includes a collection of AI agents that will be assigned to each human teammate participating in Minecraft gameplay. To carry out experiments, a specialized environment in LangLab has been set up. This environment is equipped with cameras and microphones that capture facial expressions and speech, as well as various sensors such as fNIRS (Functional Near-Infrared Spectroscopy), EEG (Electroencephalography), EKG (Electrocardiogram), and GSR (Galvanic Skin Response) which gathers physiological data.

All experimental data is recorded within a controlled local environment, where participants engage in individual and team tasks and are allowed verbal communication. Through this setup, the project can gather comprehensive data on the interactions and behaviors of the participants, which will inform the development of effective AI agents for teamwork.

Referring to Fig. 2, each experiment usually comprise of 3 participants and they follow a fixed instructed paradigm containing eight different tasks done in sequence:

Rest state: The participants are requested to sit back and relax for 300 seconds.

Finger-tapping individual task: The participants tap the spacebar on the keyboard for 10 seconds.

Finger-tapping team task: The participants tap the spacebar on the keyboard for 50 seconds in sync with each other based on visual feedback.

Affective individual task: The participants see an image for a few seconds on screen and they rate it based on its arousal and valence score. This is done for a total of 15 images. This lasts for roughly 3 minutes.

Affective individual task: The participants see an image for a few seconds on screen and they rate it based on its arousal and valence score after discussing it with each other. This is done for a total of 15 images. This lasts for roughly 11 minutes.

Minecraft training mission: This is for a mission tailored to train participants based on their role as medic, transporter, and mechanic.

Minecraft Saturn A mission & H. Minecraft saturn B mission : These are two missions with different environments where participants with their roles as medic, transporter, and mechanic have to team up and collaborate to rescue critical victims placed in their environments.

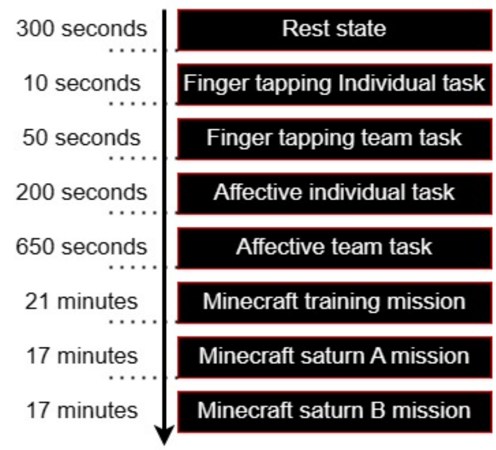

Fig. 2: ToMCAT Experimental Paradigm

The multimodal data acquisition methods for ToMCAT includes:

Functional Near-Infrared Spectroscopy (fNIRS) [17] is a technology that can identify which parts of the brain are being used during an activity. When a specific part of the brain is activated, the blood flow to that region increases. By detecting changes in the concentration of the blood in the brain, fNIRS can determine which parts of the brain are most active.

Electroencephalography (EEG) [10] is a technique used to record the spontaneous electrical activity of the brain in the form of an electrogram.

Eye tracking [9] involves the detection of the human pupil and the subsequent recording of eye movements and fixations while viewing images or any other content on screen.

Galvanic Skin Response [2] is a measure of the electrical conductance of the skin. It is also commonly known as Skin Conductance Response (SCR). GSR is a physiological measure that reflects changes in sympathetic nervous system activity, which is one of the branches of the autonomic nervous system that is involved in the "fight or flight" response.

Electrocardiography (ECG or EKG) [11] is a non-invasive medical test that is used to record the electrical activity of the heart. EKG measures the changes in electrical activity of the heart muscle during each heartbeat, providing information about the heart's rhythm, rate, and overall function.

2.2 Related Work of Visualization

Pupil Player is a crucial tool for researchers who use Pupil Capture to collect eye-tracking data. It provides a user-friendly interface for visualizing recorded data and analyzing it. Additionally, Pupil Player enables researchers to export their data into various formats, making it easier to analyze and share with other researchers. Visualization plugins include Vis Circle, Vis Cross, Vis Polyline, Vis Light Points, and Vis Eye Video Overlay. Analysis Plugins include Surface Tracker, Fixation Detector, Blink Detector, Head Pose Tracking, IMU Timeline [9].

The **nirsLAB package** is an adaptable software analysis environment designed to facilitate the examination of time-varying near-infrared measurements of tissue. It is particularly well-suited for analyzing data acquired using NIRx systems [19].

BrainVision Analyzer is used by neuroscientists to process a variety of neurophysiological data. For the ToMCAT project, EEG data is being collected. Analyzer is easy to use and offers a variety of powerful features for processing and visualizing EEG data [3].

Aurora is a software used by neuroscientists to visualize collected fNIRS data as signal view and topological view [13].

MNE Python is a Python package for exploring, visualizing, and analyzing electroencephalography (EEG) and magnetoencephalography (MEG) data. With MNE-Python, researchers can analyze various aspects of brain activity, such as event-related potentials (ERPs), oscillatory activity, and connectivity between brain regions. [5]

While various software options exist for monotonic time static analysis, they typically operate independently and focus on relative rather than actual time of experimentation. However, combining multiple modalities such as fNIRS, EEG, and eye-tracking visualizer requires a comprehensive and integrated visualization tool that does not currently exist. A thorough literature survey revealed no existing platform that seamlessly integrates fNIRS and EEG data with eye-tracking data, allowing for a comprehensive analysis of images, eye position, and brain response, which highlights the need for a novel and user-friendly visualization tool such as ToMCAT Offline Viz.

3 MATERIALS AND METHODS

3.1 Data

The data utilized in this study was obtained from LangLab, under the supervision of Dr. Adarsh Pyarelal and Dr. Kobus Barnard, and was curated by Caleb, an active member of the lab. Prior to usage, permission was obtained from the lab to ensure compliance with all applicable ethical and legal requirements.

The data consists:

Data type	**Data Description**
Experimental Images	PNG image format (Resolution: 1280x720, File size $\sim$ 600 kB) Sampled at 10 Hz
Eye Tracker	CSV Format (File size approx 140 MB) Sampled at 200 Hz
Unprocessed EEG and fNIRS	XDF Format (File size approx 500 MB)
Pre-processed and labeled fNIRS	CSV Format (File size approx 53 MB) Sampled at 10.2 Hz
Pre-processed and labeled EEG	CSV Format (File size approx 1.2 GB) Sampled at 500 Hz

3.2 Experimentation

3.2.1 Data Preprocessing of physiological data

The Lang Lab uses lab recorder software to collect physiological data and stores it in XDF file which requires parsing and conversion to a readable format such as CSV file. For each experiment, 3 XDF files are generated, one for each participant, containing EEG, fNIRS and eye-tracking data in the form of a dictionary. To process this data, a script was written that performs the following tasks:

1. Reads all XDF files.
2. Iterates through all Physio streams individually. This includes defining montage based on the physio stream(10-05 for EEG and x,y coordinates from NIRS part of XDF file.)
3. Reads start and stop time stamps from XDF file. Uses these timestamps to create a date-timestamp distribution.
4. Creates a data frame with all the physio stream data with the date-timestamp distribution.
5. Creates a label distraction from start to stop timestamp Baseline task and Minecraft metadata. Then, syncs all this information with data frame.
6. Removes data before start and stop time stamps from XDF file.
7. Exports the data frame as CSV file and pickle file.

Overall, this script enables the efficient processing of physiological data for the Lang Lab's experiments, allowing for easier analysis and interpretation.

The fNIRS data contains a lot of physiological noise such as heartbeat, breathing, and other motion artifacts, which need to be filtered out. To remove these physiological noises a script was developed that implements a Butter-bandpass filter. The low-pass filter was set to 0.01 Hz and the high-pass filter was set to 0.2 Hz. This filtering process effectively removes unwanted noise from the data, resulting in a cleaner and more accurate representation of the fNIRS signals.

The EEG data often contains extraneous noise from the environment that must be eliminated. To address this, we utilized MNE-Python's built-in filter function, configuring lowpass and highpass thresholds to 1 Hz and 30 Hz, respectively. Additionally, we employed another MNE-Python function to segment the data into discrete frequency bands.

3.2.2 Approach & Techniques

Eye Tracking with gaze fixation:

Fig. 3 shows a screenshot superimposed with the eye position that signifies the gaze fixation of the participant on the screen.

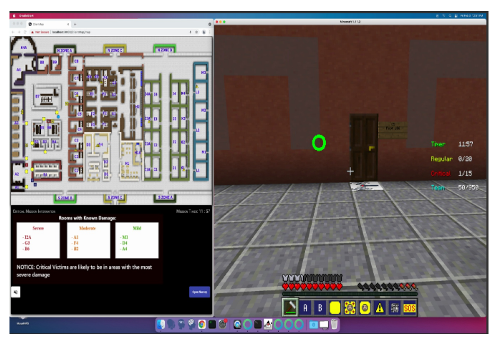

Fig. 3: Screenshots with pupil position denoted by the green circle.

The calculation of gaze position coordinates on the screenshots involved the following steps:

1. Create a grid with a resolution of 720 by 1280 to match the screenshot.
2. Import gaze.csv as a dataframe.
3. Extract the "norm_pos_x" and "norm_pos_y" columns from the dataframe and assign them to "x" and "y", respectively.
4. Transform "y" values by subtracting them from 1.
5. Scale "x" values by multiplying them with the second element of the "grid" tuple and "y" values by multiplying them with the first element of the "grid" tuple.
6. Return the modified "x" and "y" values.

Once the x and y coordinates are calculated, the gaze position is plotted using the cv2.circle function from the opencv-python package.

We have used this approach because superimposing eye data onto screenshots, along with a time slider, enables the analysis of temporal aspects of visual attention and eye movement patterns. It provides a comprehensive way to visualize and explore how visual attention changes over time.

Techniques: The applied technique for Superimposed Gaze Fixation involves overlaying gaze fixation positions onto the screenshots by plotting them as circles or markers at the corresponding coordinates. This visualization technique allows for a clear visual representation of where team members directed their visual attention. Additionally, the combined eye-tracking data and screenshots enable users to compare and analyze the focus areas of team members. The interface supports the exploration and extraction of valuable insights from the integrated eye-tracking data with fNIRS or EEG. Users can identify patterns, relationships, and trends pertaining to eye movements.

This technique can be combined with a time slider presenting a valuable tool for examining the temporal dynamics of visual attention. By incorporating a time slider into the eye-tracking visualization, researchers and analysts can investigate the evolution of visual attention over time, monitor eye movements at various time intervals, and gain insights into the patterns and fluctuations of attention.

fNIRS Signal View: Fig. 4 shows a signal view of the fNIRS data across 20 channels over a window of 200 samples.

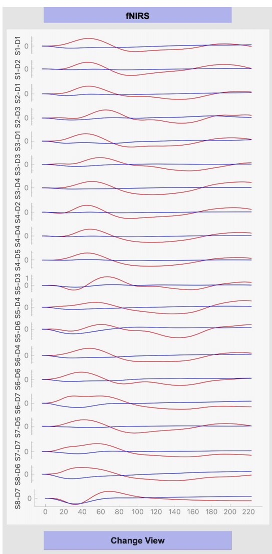

Fig. 4: Signal view of fNIRS where red denotes HbO data and blue denotes HbR data.

Here are the steps to plot fNIRS data:

1. Import "NIRS_filtered.csv" as a data frame.
2. Separate the data frame into two parts: HbO by selecting columns 1 to 21, and HbR by selecting columns 21 to 41.
3. Define a pen for each data frame using pyqtgraph, assigning red to HbO and blue to HbR.
4. Plot each column of HbO against the corresponding column of HbR, repeating this process for all columns in the data frame.

Techniques: For generating the signal view of fNIRS data, line plots were utilized. The standard approach [16] to visualize signal view of fNIRS data is Line plots which offer a clear visualization of the processed HbO and HbR signals over time, enabling researchers to analyze the temporal dynamics of brain activity.

By representing the HbO and HbR signals as distinct line plots, researchers can easily observe changes in hemoglobin concentration and obtain insights into neural activity and brain oxygenation levels. Line plots provide the advantage of identifying trends, fluctuations, and patterns in the data, facilitating the analysis of different brain states.

The use of line plots in the signal view of fNIRS data allows for comparison and analysis, enabling researchers to investigate the relationships between HbO and HbR measurements. This technique fosters a comprehensive understanding of the temporal aspects of brain activity and supports the exploration of neural processes and cognitive functions associated with fNIRS data.

EEG Signal View: Fig. 5 shows a signal view of the EEG data across 21 channels over a window of 200 samples.

To plot EEG data, follow these steps:

1. Use the pyxdf library to load the eeg_fnirs_pupil.xdf file.
2. Filter the data to select only EEG data using the stream['info']['type'][0] parameter.
3. Exclude EKG and GSR channels from the data.
4. Apply a filter to the EEG data using the mne.filter() function, setting the l_freq and h_freq parameters to 1 and 30, respectively, and using the skip_by_annotation='edge' and picks=['eeg'] options.
5. Store the filtered EEG data in a data frame.
6. Define a pen for each column in the data frame using pyqtgraph, assigning black to all EEG channels.
7. Plot each EEG channel of the data frame.

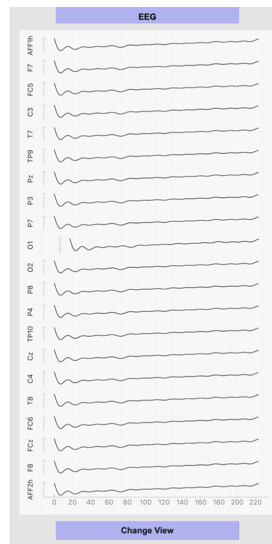

Fig. 5: Signal visualization of the EEG data captured by 21 channels, spanning a window of 200 samples.

Techniques: To generate the signal view of EEG data, line plots are considered the most suitable technique, which is also the standard approach defined [8]. Line plots represent the processed electrical activity as a line graph, where the y-axis represents microvolts (mV) and the x-axis represents time. This visual representation allows researchers to easily observe the fluctuations and patterns in electrical brain activity, enabling analysis of different brain states.

Line plots offer several advantages in visualizing EEG data. They provide a clear and concise representation of signal trends and anomalies, making it easier to identify important features in the data. By visually displaying the temporal dynamics of electrical brain activity, researchers can gain insights into the changes and variations occurring in the EEG signals over time. Furthermore, line plots facilitate the comparison and analysis of different EEG signals, allowing for a comprehensive understanding of brain activity.

Therefore, we found line plots as the optimal technique for generating the signal view of EEG data. Their ability to provide clear visualizations of the data over time enables the analysis of temporal dynamics, identification of patterns, and comparison of different brain signals. By leveraging line plots, researchers can effectively explore neural processes and cognitive functions associated with fNIRS and EEG data.

fNIRS Topological View: Fig. 6 Shows topological view of mean of fNIRS data for HbO and HbR data over a window of 100 samples.

To generate a topological plot of fNIRS data, follow these steps:

1. Use the pyxdf library to import the eeg_fnirs_pupil.xdf file.
2. Filter the data to select only NIRS data using the stream['info']['type'][0] parameter, and store it in a data frame.
3. Retrieve the sampling frequency by accessing stream['info']['desc'][0]['montage'][0]['sampling_rate'][0], and save it as 'sfreq'.
4. Extract the source and detector locations from the stream. This can be done by accessing the following paths:

   stream['info']['desc'][0]['montage'][0]['optodes'][0]['sources'][0]['source']

   stream['info']['desc'][0]['montage'][0]['optodes'][0]['detectors'][0]['detector']
5. Segment the data frame into HbO by selecting columns 41 to 61, and HbR by selecting columns 61 to 81.
6. Calculate the mean of the HbO and HbR data across a sliding window of 200 samples.
7. Use the mne.viz.plot_topomap package from the MNE-Python library to separately plot HbO and HbR, along with a color bar, to generate a topological map.

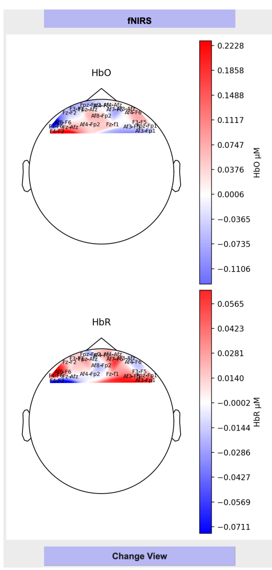

Fig. 6: Topological visualization for fNIRS data for HbO and HbR data.

Techniques: When generating the topological view of fNIRS signals, a widely used technique is to interpolate the values at each sensor location, resulting in a smooth 2D map that visually represents the spatial distribution of the data across the sensor array [20].

For fNIRS data, the topological view is valuable as it allows researchers to observe the spatial patterns of brain activity. The interpolated values reveal regions of higher or lower activity levels, providing insights into the distribution of oxygenation and hemodynamic changes across the scalp. Color is often used to represent different activity levels, aiding in the identification of regions of interest and analysis of spatial patterns.

The availability of a switch between the signal and topological views is crucial for analysis. Researchers can toggle between the two representations based on their preferences and goals. This flexibility enables them to focus on specific aspects, such as trend analysis or comparing activity patterns across conditions or participants. By providing both views, researchers gain a comprehensive understanding of the data, examining both the temporal dynamics and spatial distribution of brain activity.

EEG Topological View: Fig. 7 Shows a topological view of the mean of EEG data over a window of 2500 samples.

To generate a topological plot of fNIRS data, follow these steps:

1. Use the pyxdf library to import the eeg_fnirs_pupil.xdf file.s
2. Filter the data to select only EEG data using the stream['info']['type'][0] parameter.
3. Exclude EKG and GSR channels from the data.
4. Apply a filter to the EEG data using the mne.filter() function, setting the l_freq and h_freq parameters to 1 and 30, respectively, and using the skip_by_annotation='edge' and picks=['eeg'] options.
5. Retrieve the sampling frequency by accessing stream['info']['desc'][0]['montage'][0]['sampling_rate'][0], and save it as 'sfreq'.
6. Set the montage using mne.channels.make_standard_montage and set it to 'standard_1005'.
7. Break up the filtered data into different frequency bands like 'delta': (1, 4), 'theta': (4, 8), 'alpha': (8, 14), 'beta': (14, 31), and 'gamma': (31, 50) using filtered_raw.copy().filter and set l_freq, h_freq based on the frequency band.
8. Use the mne.viz.plot_topomap package from the MNE-Python library to separately plot for each of the frequency bands, along with a color bar, to generate a topological map.

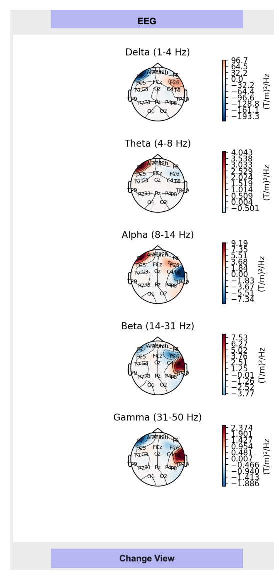

Fig. 7: Displays a graphical representation of the average EEG data over a 2500-sample window in a topological format for 21 channels.

Technique: The common approach for visualizing the topological view of EEG signals involves interpolating the values at each sensor location [4]. This interpolation technique generates a smooth 2D map that visually represents the spatial distribution of the data across the sensor array.

The topological view shows the spatial distribution of electrical brain activity. Interpolating the electrical signals from EEG sensors creates a map highlighting scalp areas with higher or lower activity. Color encoding represents different levels of electrical activity, aiding the interpretation and analysis of activity intensity at different scalp locations. This visualization technique enables researchers to understand the topographical organization, identify activation patterns, and explore functional connectivity between brain regions.

A switch between signal and topological views is important for analysis. Researchers can toggle between the two representations, focusing on specific aspects such as trend analysis or comparing activity patterns across conditions or participants. By providing both views, researchers gain a comprehensive understanding of the data, examining both temporal dynamics and spatial distribution of brain activity.

Slider: The slider is used to regulate experimental playback that helps in transition between different states during a specified timestamp range, displaying the fluctuation in fNIRS and EEG signals across various channels in response to changes in the participant's gaze position on the screenshots.

The slider feature facilitates smooth transitions between different views, allowing for seamless switching between the signal and topological representations. As the slider is adjusted, both the signal and topological views dynamically update, providing real-time visualization of the fNIRS and EEG data. This interactive functionality enables researchers to explore and analyze the temporal and spatial aspects of brain activity, enhancing the understanding of the dynamic relationships between eye movements and neural responses.

4 Results & Evaluation

4.1 Results

Observations from Rest state:

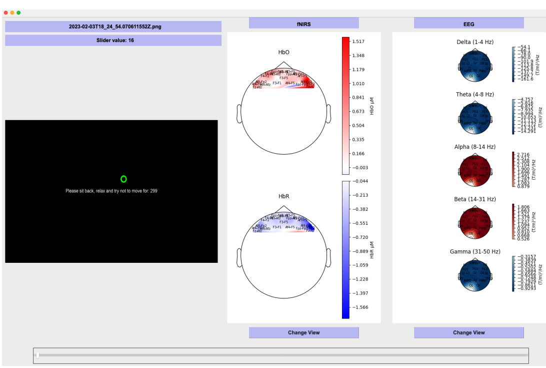

Fig. 8: Visualization for fNIRS and EEG at the start of Rest state.

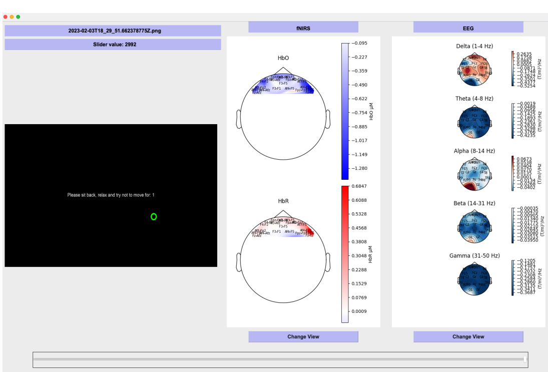

Fig. 9: Visualization for fNIRS and EEG at the end of Rest state.

Fig. 8 marks the beginning of the rest state, during which fNIRS topological plots reveal high HbO values, indicating increased activation in the right frontal cortex.Fig. 9 smarks the end of the rest state, during which fNIRS topological plots reveal high HbO values that suggest decreased activation in the right frontal cortex. This finding is consistent with previous research on reduced activation during the rest state [6,7].

Another noteworthy observation from Fig. 9 is the activation in the Beta frequency bands observed in the EEG topological view. This finding aligns with a previous study on rest state [1]

Observations from affective task: Fig. 10 and Fig. 11 illustrate continuous activation in the frontal cortex throughout the affective task of rating the 'snake eating the frog' image, from start to finish. This maybe because this area of the brain also plays a role in decision-making and behavioral responses, which may be necessary when evaluating the emotional content of a stimulus which aligns with previous studies on cognitive load during affective task [14] However, the EEG activations fluctuated over time.

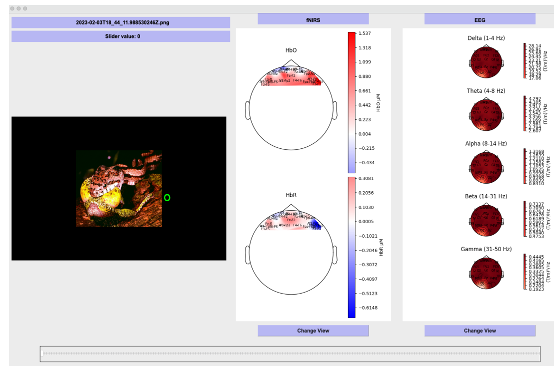

Fig. 10: Visualization for fNIRS and EEG at the start of Affective state.

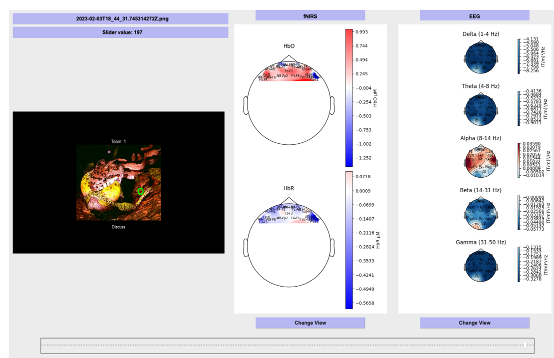

Fig. 11: Visualization for fNIRS and EEG at the end of Affective state.

Observations from Minecraft mission:

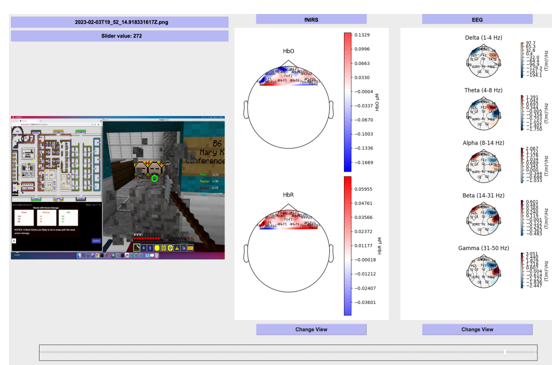

Fig. 12: Visualization for fNIRS and EEG during the Minecraft mission.

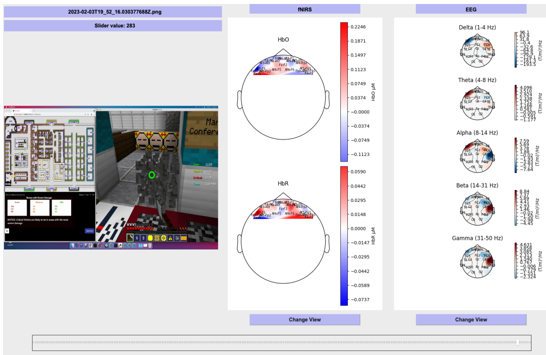

Fig. 13: Visualization for fNIRS and EEG towards the end of Minecraft mission.

From fNIRS topological plots of Fig. 12 and Fig. 13 we observed significant activation in the left prefrontal cortex, which may be explained by the activation of the left somatosensory region due to motor activity. Since the participant was using their right hand to click a mouse, the observed activation in the left prefrontal cortex is consistent with previous studies on the activation of the somatosensory region during motor actions [12].

Another interesting observation from the EEG topological plots in Fig. 12 and Fig. 13 is the activation in the right temporal region in the alpha frequency band. This may be explained by the fact that the subject, who is an engineer, is being called out by either a medic or transporter to clear rubble from the room. As the temporal lobe is responsible for auditory processing, we can see activation in this region during the task, this is supported by previous studies on activation in temporal region due to auditory stimuli [15].

4.2 Evaluation

To assess the effectiveness of the project, we obtained feedback from two social scientists regarding their experience with the tool.

Comments from Social Scientist 1 (Diheng Zhang) :

"*I think this is a cool, prototype-liked visualization of fNIRS and EEG. I like the idea that you have the screen, focal point, fNIRS, and EEG all synced up, and it helps compare brain activities frame-by-frame. If I give any suggestions, I would like to see the calculation parameter clearly labeled on the screen. (Like, what is the width of the sliding window you used for the averaging, what types of filters were applied before the visualization, etc., because it will help the user make sense of the visualization.) It will be even better if the user can set those parameters in the GUI and change the visualization with them as input, but I have no idea if that will be feasible with your program. Overall I like it a lot and it is impressive!* "

Comments from Social Scientist 2 (Eric Andrews) :

" *I think this looks pretty cool! Additionally, it would be a cool add-on to have not only the information for the current time point but also an average response for the entire range of the task that you're looking at.*"

Together with this, we received positive verbal feedback from Computer Scientists.

4.3 Technology

Programming language: Python 3.9

Libraries: PyQt, CV2, Pandas, Matplotlib, MNE-Python PyQt5 is a cross-platform GUI toolkit that will help us to develop an interactive desktop application. CV2 is an OpenCV package for Python that serves for image loading, image compression, etc. Pandas will be used to load data from CSV files allowing the working of "relational" or "labeled" data. QtGraph is a graphical user interface (GUI) library which helps in creating line plots.

Matplotlib would allow us to create static, animated, and interactive visualizations. MNE-Python is used for a topological view of the brain for EEG and fNIRS signals. QtGraph is used to visualize signal views with customizable tools such as reordering of channels.

4.4 Code Execution

To run the code and generate results, follow the steps below:

- Create a virtual environment and run the command

```
pip3 install -r requirements.txt
```

- In order to run the application

```
python3.11 main.py
```

A separate drive link (`https://drive.google.com/drive/folders/1WodB5uRgMqt6ytaAWTBF7oI-V685VYUl?usp=sharing`) has been provided due to the dataset's substantial size of approximately 2 GB. The link contains a zipped file that includes both code and data information.

The original dataset, which includes data for three subjects, is 116 GB in size. However, for the purpose of this project, a reduced version of the dataset for one subject has been created, which is only 2 GB in size.

4.5 Deviations from Project Milestone 2

Throughout the project, we have adhered closely to the original proposal. As we made progress, we completed the signal view of EEG data. We successfully achieved this milestone and subsequently proceeded to develop the topological view for both types of data. To achieve the motive of our project, we synchronized all modalities effectively. By completing both the signal and topological views and ensuring synchronization, we have significantly enhanced the quality and utility of the final product. These accomplishments have provided us with a comprehensive understanding of the data and enabled us to make informed decisions during the design and implementation process.

4.6 Timeline

Milestone 1: We developed a skeleton visualization tool that enables us to scrub through the timeline and visualize screenshots like video playback.

Milestone 2: The eye positions have been overlaid onto the screenshots, allowing us to observe shifts in gaze location and corresponding changes in screenshots as we navigate through the timeline.

Milestone 3: We have added a different section that shows a signal view for fNIRS signals which is currently decoupled with the eye-tracking data.

Milestone 4: We created a separate section that displays a line plot of EEG data. Both fNIRS and EEG data are synced with the eye tracking data based on timestamps.

Milestone 5: Added a section to the right that shows the topological view for fNIRS signals along with a button to toggle between the topological view and signal view.

Milestone 6: Similarly, another section is added on the right-hand side that presents the topological view of EEG signals, accompanied by a button to switch between the topological and signal views.

Milestone 7: Worked on the project report by presenting comprehensive information regarding the project's scope, objectives, methodology, findings, and recommendations in a clear, concise, and structured manner.

Milestone 8: Worked on completing the project report contents as well as preparing the project presentation.

Project Milestones

Milestone	Description
March 17	Skeleton of the viz tool (Basic structure design)
March 24	Eye positioning for gaze fixation
March 29	Progress Update with the addition of fNIRS signals
April 7	Adding EEG signal view using line plot
April 14	Topological view implementation to switch from signal view
April 21	Project Initial Report of viz tool with defined subsections
May 3	Final Report Completion

4.7 Team Member Roles

Caleb is a member of the ToMCAT project, he is involved in data preprocessing of the physiological data and syncing it with the timestamps of the task done during the experiment. Apart from this, he has completed the skeleton structure of the tool which includes the slider. He developed the topological view of fNIRS data and EEG data. Harshita is involved in translating the surface coordinates of the eye-tracking data to the resolution of the screenshot and superimposing it on the top of the screenshot. She worked on development of the signal view of EEG data and linking it with the slider. Apart from this, she linked the base slider with EEG topological view. Rupal is involved in the development of the signal view of the fNIRS data and linked to the slider. She is involved in syncing the slider with topological view of both fNIRS. Apart from this, she complete the designing of the UI and fixing the layouts to achieve the proposed view of the application.

5 Conclusions

Our research introduces "ToMCAT Offline Viz," a new visualization tool that combines eye-tracking, fNIRS, and EEG data to gain comprehensive insights into team dynamics. By overlaying eye-tracking data onto screenshots and displaying fNIRS and EEG data alongside, researchers can analyze visual attention and neural activity simultaneously.

The tool offers signal and topological views of the data, along with a synchronized slider for comparing continuous changes. It addresses the need for user-friendly tools in studying cognitive and neural mechanisms, empowering researchers to understand team coordination better. This innovative tool has implications for AI agent development and global team optimization. Its contribution to the field of cognitive and neural mechanisms of teamwork is significant.

6 Lessons Learned

The development of the "ToMCAT Offline Viz" tool for data visualization has provided several important lessons in this field. First and foremost, it has highlighted the significance of integrating multiple modalities to gain a comprehensive understanding of complex data.

Another lesson learned is the importance of effective data preprocessing and filtering techniques. Preparing the data by removing noise and artifacts ensures that the visualizations accurately represent the underlying signals and facilitate meaningful analysis. This step helped us in learning the cruciality for obtaining reliable and interpretable results.

Additionally, we intended to add interactions by synchronizing the slider feature that has provided a powerful tool with varying aspects of the data. This helped us in learning how the variations in patterns by fluctuations over time can enable the identification of temporal patterns and relationships between variables

These lessons in data visualization can inform future developments in this field, emphasizing the importance of multimodal integration, data preprocessing, user-centric design, flexible visualization views, temporal analysis, and interdisciplinary collaboration. By applying these lessons, researchers can create advanced visualization tools that enhance data understanding and drive further insights in various domains.

7 Future Work

In order to enhance the tool's functionality, we plan to extend its support to three subjects. Additionally, we aim to provide a customizable GUI that allows users to input parameters such as channel exclusion, frequency band selection, and sliding window size for topological view. Furthermore, we aim to display the parameters set for the current visualization to enhance the user's understanding of the tool's functionality.

8 Ethics

To maintain confidentiality, all members of the team have signed a Non-Disclosure Agreement with The University of Arizona eIRB, which restricts the sharing of actual data to only the ToMCAT team members. Rupal and Harshita have completed the relevant CITI and COI training to obtain access to the data.

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