MNE-Python: Time-Frequency Volumetric Source Space Viewer

About me

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Code contribution

- https://github.com/mne-tools/mne-python/pull/9586
- https://github.com/mne-tools/mne-python/pull/6910
- https://github.com/mne-tools/mne-python/pull/10432
- https://github.com/mne-tools/mne-python/pull/10493
- https://github.com/mne-tools/mne-python/pull/10407
- https://github.com/mne-tools/mne-python/pull/10401
- https://github.com/mne-tools/mne-python/pull/10373
- https://github.com/mne-tools/mne-python/pull/10212
- https://github.com/mne-tools/mne-python/pull/10202
- https://github.com/mne-tools/mne-python/pull/10185

Project information

1. Sub-org name

MNE-Python

2. Project Abstract

Transforming electrophysiology signals from sensors into their frequency representations has been shown to be a way to increase the power for application of this data; for one example of very many see Swann et al., 2015. This Fourier-transformed sensor data can be used to infer data within the brain in a very similar way as the time-series data but with an added, fifth dimension for frequency. MNE-Python has all the components necessary for time-frequency source estimate viewing and would be greatly improved by integrating them to allow for exploration of this complex data. A graphical user interface (GUI) that allows users to look at regions of high power spectral density, while letting the user dynamically adjust the range of frequencies, would be incredibly helpful for allowing this kind of data to be explored and analyzed. The ability to browse slices has already been implemented in `mne.gui.ieeg_locate` and could be abstracted to be used in this case. Time-frequency plotting of spectrograms, with appropriate units and baseline correction already exists in MNE-Python as well. Putting these elements together into a GUI would be a great improvement for the MNE-Python tool and community.

3. Detailed description

<u>Introduction</u>

Electrophysiology data can be decomposed into frequency components across time, which has been shown to be an effective approach for analysis (Miller et al., 2007). This time-frequency data, collected at the scalp using magneto- and/or electroencephalography (MEG and EEG), can be used to estimate oscillatory activity within the brain using techniques like minimum norm estimation (MNE), dynamic statistical parametric mapping (dSPM) and exact and standardized low resolution brain electromagnetic tomography (eLORETA and sLORETA) (Gramfort, 2013), beamforming (Dalal et al., 2008) and their derivatives. Source estimation techniques are widely used in electrophysiology research but are generally done on time or frequency data that has not been decomposed into time-frequencies. Adding a frequency dimension as well as time adds another order of magnitude of compute time but, more importantly, adds a fifth dimension (in addition to the three spatial dimensions and time) which is difficult to visualize. Time-series source data can be viewed on an inflated brain as in (https://mne.tools/dev/auto_tutorials/stats-source-space/60_cluster_rmANOVA_spatiotemporal.html) at a time-point of interest or in a video across time points. Although it is difficult to see the entire source estimate at all source vertices at once because of occlusion from nearer vertices, multiple views can give a reasonable image of brain activity of interest. The extension to time-frequency data on the surface of the brain is relatively straightforward; the magnitude of the time-frequency data, either averaged or in a frequency band of interest, can be plotted in lieu of the magnitude of the source estimate in time. Given the constraints of 2D viewing, plotting a volumetric source estimate is most amenable to being viewed superimposed on anatomical magnetic resonance (MR) brain slices images e.g. (https://mne.tools/dev/auto_examples/inverse/compute_mne_inverse_volume.html). These plots of dynamic functional activity are best viewed interactively, especially with the added complexity from visualizing a power time series, and ideally being able to toggle between different frequency bands of interest in real time and adjust the bounds of the band; a single image or even video is not able to capture the complexity from the dimensionality of this data.

Workflow

The user will be able to follow existing tutorials to compute a surface or volume source estimate (e.g. https://mne.tools/dev/auto_tutorials/inverse/40_mne_fixed_free.html) from raw electrophysiology data (MEG, EEG or intracranial EEG). Then the user will be able to interact with the plots and GUI from this project to visualize and explore their data. Finally, the user will be able to follow other existing tutorials (e.g. https://mne.tools/dev/auto_tutorials/stats-source-space/60_cluster_rmANOVA_spatiotemporal.html) to make statistical inferences about their data motivated by their explorations.

CLI/API

A possible command line call might look something like this:

```
$ mne plot_stc --stc /path/to/stc.h5 --subject sample \
    --subjects-dir /path/to/Freesurfer/subjects_dir
```

The Python API will be documented with Sphinx in the style of MNE and syntax will look like this:

```
>>> stc.plot()
```

where the PyQt user interface will be launched instead of pyvista brain plots for volume source estimates.

Implementation Details

Some notes on potential implementation roadblocks and challenges along with potential solutions are outlined below:

- Source estimate data (*stc.data*) that is 3D (ch x time x freq) instead of 2D (ch x time) will have to be checked in all the functions where this is used. By using inheritance and putting check functions in the base classes, the number of changes should be able to be minimized.
- Source estimate data that is 3D will ideally be saved to the *hdf5* file format but 2D data is

currently saved. Having optimally sized files may be an issue, but, by paring down fields in the stc class, a reasonable file size is likely to be achieved.

4. Weekly timeline

June 13, 2022 - June 17, 2022
- Refactor source estimate data (*stc.data)* to support time-frequency data (add frequency dimension)

June 20, 2022 - June 25, 2022
- Continue refactor, with tests, documentation and checks for backward compatibility

June 27, 2022 - July 1, 2022
- Add time-frequency to *stc.plot* to replace the line plot

July 4, 2022 - July 8, 2022
- Refactor to abstract the intracranial GUI slice browser (uses the same navigation of volumetric data)

July 11, 2022 - July 15, 2022
- Implement a GUI with a slice browser and time-frequency plot

July 18, 2022 - July 22, 2022
- Implement a GUI with a slice browser and time-frequency plot

July 25, 2022 - July 29, 2022
- Write tests

August 1, 2022 - August 5, 2022
- Write tests

August 8, 2022 - August 12, 2022
- Write examples and documentation

August 15, 2022 - August 19, 2022
- Write examples and documentation

August 29, 2022 - September 2, 2022
- Write examples and documentation

September 5, 2022 - September 12, 2022
- Write examples and documentation

Conclusion

The software implementation required to execute this project is relatively well-known. Therefore, I expect there to be time to increase usability by writing ample tests and documentation. This project will improve the ease of exploring time-frequency source estimate data, making it more accessible for analyses. Furthermore, it will allow for visualization that will aid in developing intuition for the relationship between sensor data and source estimations, making it an important didactic tool as well as a tool for data exploration.

References

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