Analysis of Acute Cognitive Impairment using Temporal Response Functions

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***Abstract*—Acute cognitive impairment in children as a result of trauma follows as the third state in mental decline, after vegetative and confused states. These patients are unable to physically interact with the world, but we can still make use of neural recordings to probe higher functions in the locked in patient. This is especially important in efforts to help the patients interact with the world using brain computer interfaces. We analyze the EEG data in response to a language listening task using spectral analysis and temporal response functions. with a comparison between forwards and reverse stimulus, and we note a clear difference between the two, indicating evidence of comprehension at a higher level. Our hypothesis is that passive language listening will index higher cognitive function.**

***Index Terms*—temporal response functions, EEG, BCI, language listening, spectral analysis**

I. Introduction

Acute Cognitive Impairment is a result of physical trauma and is the stage that immediately follows vegetative and confused states []. In it, the patient is said to be locked in and is unable to interact with the environment. However, there is evidence that higher cortical functions are still there, and probing them is a first step to building suitable brain-computer interface based interaction platforms for rehabilitation.

Broadly speaking, spectral and temporal analysis are two avenues for analysis of speech and EEG data that goes along with it [1].There has been some work on using spectral analysis of EEG data to probe for awareness in patients with severe brain injury [2], and most such works use healthy controls as a reference. However, this does not account for inter-patient variation and often shows differences that can't be used to support awareness, and in this work we try a different kind of control, where we pass the stimulus in a reversed fashion and get recordings in response to it. Moreover, spectral analysis does not give us exhaustive information about cognitive functions, for which other methods like temporal response function (TRF) analysis [3] [4] and semantic TRF analysis [5] have been devised, which generally fare much better. Another problem with using spectral analysis is that although it works very well for adults, it is found to work only in some cases in children, possibly because of development differences [6].

II. Methods

EEG responses are recorded from a dry electrode kit during passive listening to chapter one of Alice in Wonderland, by Lewis Caroll. The stimulus is first played forwards and then reversed (150 seconds each), so that the overall frequency content of the stimulus remains the same, but the forwards has underlying meaning whereas the reversed doesn't. For this experiment, we have a cohort of 44 patient data with both forwards and reversed recordings.

We devise a pipeline for analysis of the above described EEG data. For a basic analysis of the stored information content, we chop up the recorded forwards and reversed data into 3 second epochs and calculate the spectra of each of these epochs for each electrode. We visualize this in the form of error bars to get an idea of how noisy the data is. This is especially important as the data is recorded from a dry electrode kit with the child possibly not paying attention for parts of the recording. To actually glean information and see spectral differences between forwards and reversed, we clean up the data by manually scrolling through the waveforms and removing bad epochs. Another alternative is to use a robust spectra estimator on the raw data itself, but we usually find that for most patients manual cleaning performs better, while retaining information. Upon visualizing the cleaned spectra in a similar way, we run a significance test analysis between forwards and reversed spectra across frequency bands and note regions of difference across electrodes. A consistent differential response is an indicator of comprehension of the meaning in the stimulus.

Spectral analysis is a simple first step in analyzing whether there is any information encoded (bump in the alpha band 8-12 Hz) in the EEG data and whether there is a notion of comprehension (spectral difference between forwards and reversed). However, due to its simplicity, it lacks the power to give a complete understanding of the EEG response. One common practice, that we also explore in this work, is to make use of Temporal Response Functions (TRFs). These are basically functions for every electrode that map the envelope of speech to the recorded neural response by a filtering (convolution) operation. This is then formulated as a matrix multiplication and the TRF transfer function is estimated using machine learning. The speech envelope is estimated as the average of the spectrogram across frequencies. From an initial sampling rate of 44.1 kHz, it is brought down to 100 Hz so as to match the output (the EEG response). The EEG response itself is sampled at 300 Hz, but is then downsampled to 100 Hz to make the training of the TRFs easier by reducing matrix size. Besides, all of the information encoded in neural data is restricted to less than 50 Hz.

As mentioned earlier, the whole experiment takes about 5 minutes, so its fair to assume that the child would not be paying attention for some time or the electrodes might have noisy recordings. Keeping this in mind, the training of the TRFs is done by dividing the data into parts and using k-fold cross validation [7] and then taking the average of the k resultant TRFs. These are presented with their corresponding correlation r-values that provide significance values for the TRF. A good measure to test if there is any information in the TRFs is to compare the TRF r-values for each electrode to those generated from a null distribution via a t-test. The null distribution TRF is estimated by shuffling around the envelope segments and passing it to the training function. A more basic way to see the difference wrt. a null distribution is to perform reconstruction of the stimulus envelope using the trained TRFs and performing a t-test on the reconstruction r-values.

Although the use of TRFs to analyze differences makes a lot of sense in this scenario, we have neglected a very important aspect of the stimulus, that it consists of actual words and semantics that may add a lot of imformation as far as comprehension is concerned. This leads to the idea of semantic TRFs, which is where much of our current efforts are directed. Instead of using the envelope of the speech, a gaussian kernel convolved impulse train of semantic dissimilarities at word onsets is used to train the (semantic) TRFs, as in [5]. For this purpose, we use the 25D GloVe semantic vectors [8] pre-trained on Twitter posts.

III. Results

From the cohort of 44 patients, we were able to observe a spectral difference between forwards and reversed in only 2 of them. This could be because of the quality of the EEG data, or because there really isn't any difference to see (which would make for an interesting observation, since this difference is clearly seen in adults). However, the likely reason for this is that spectral analysis is insufficient in its simplicity. The following results have been presented for one of the patients in which we saw a spectral difference. Fig. 1 shows a headplot (arranged according to electrodes) with power spectra of 3 sec epochs for the raw data, which is compared to Fig. 2 after cleaning of bad epochs. Fig. 3 shows statistical spectral difference bands and we can clearly see that the forwards response has more power in the 8-10 Hz band in the P4, Pz, T5, T6, O1 and O2 bands, as compared to reversed, which is meaningless (although has the same frequency content). Moreover, since this difference is mainly seen in the parietal and temporal regions, this indicates possible comprehension of the speech.

Fig. 4 shows the headplot for the TRFs of forwards vs. reversed for $k = 5$ folds. We see typical TRFs with similar structure in most electrodes and a clear difference in forwards vs. reversed, noting a recurrent peak in the forwards response. In Fig.5 we note the TRF r-values for each electrode across the folds when compared to the 3σ value of the null distribution. This is quantified in the form of a t-test for each electrode, which is shown in Fig. 6. Unfortunately, both the t-tests rule most of our TRFs as insignificant, and more so, the ones that are significant are mostly in the reversed data. This means that we can't be confident about the TRF differences that we are seeing in Fig. 4, and leads us to explore other avenues, like incorporating the meanings of words and context in semantic TRFs.

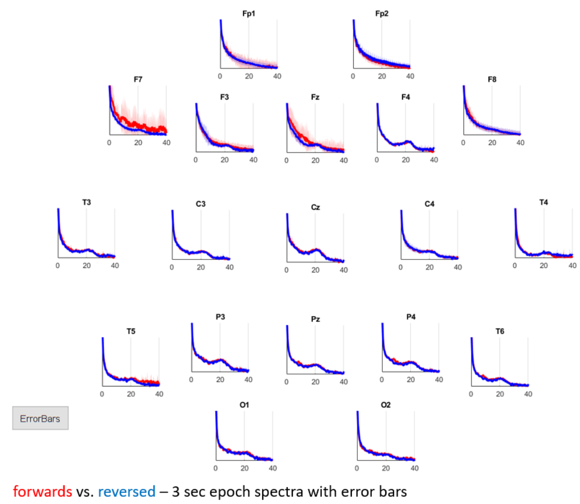

Fig. 1. Power spectra headplot for forwards vs. reversed for 3 second epochs of raw data.

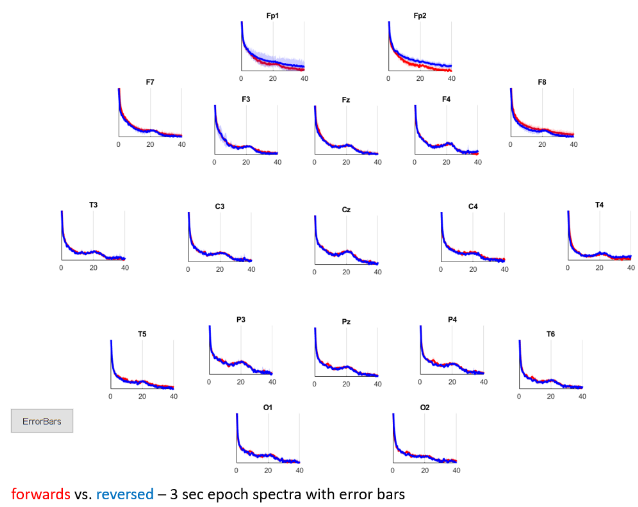

Fig. 2. Power spectra for forwards vs. reversed for 3 second epochs of cleaned data.

IV. Discussion & Future Work

In our work, we have explored the ideas of spectral analysis and TRF analysis to support our hypothesis that "passive language listening indexes cognitive function". We are able to see a spectral difference in forwards vs. reversed response for 2 out of 44 patients only, which is what leads us to explore other methods like TRF and semantic TRF analysis. The TRF analysis looks promising, but the r-values deem the TRFs insignificant. One possible reason for this is that we have very little data - each recording is 150 secs long, which when divided into 5 folds is barely 30 secs long, which is very little data to train TRFs upon. Our current efforts are in getting around this obstacle by strategies like bootstrapping. Another direction of work that we are pursuing

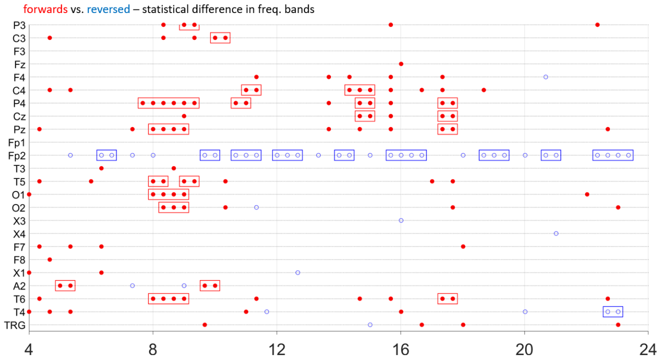

Fig. 3. Statistical spectral difference across frequency bands and across electrodes. A red or blue dot indicates that the forwards or reversed power is more in that band for that electrode, respectively. Continuous such bands are grouped together in a box to show regions of spectral difference.

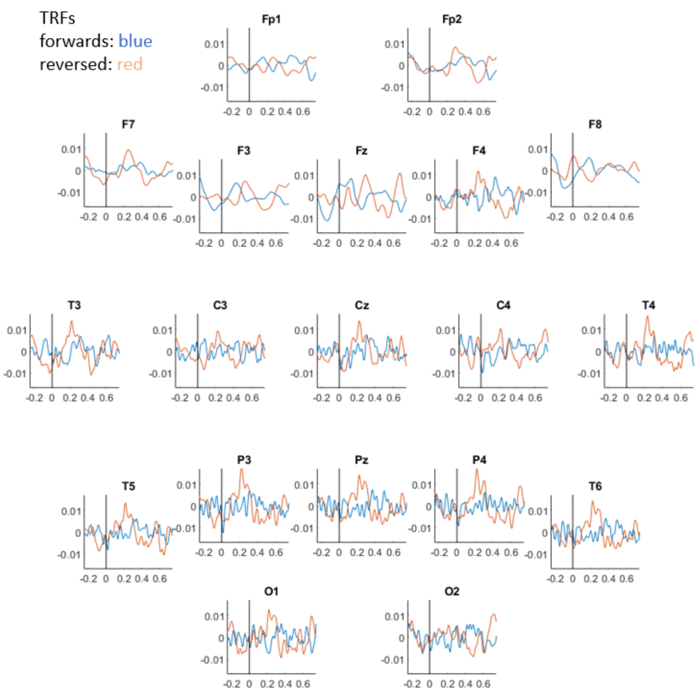

Fig. 4. TRF headplot for forwards vs. reversed as an average over 5 folds for every electrode.

is to make use of the semantics of the sentences to probe more information from the EEG recordings. This is done using the semantic dissimilarities of any given word semantic vector to it's previous context, which is the average of all the word vectors preceding it in the sentence. At a more basic level, there is a problem that we are passing raw data to the TRF algorithm (since we can't remove epochs as it would lead to discontinuities in the stimulus). One way to get around this is to use Artifact Subspace Reconstruction [9] to clean the data, which is another direction to pursue in the upstream portion of the pipeline. There is a possibility of designing a better experimental paradigm, where we use scrambled stimulus as a control, instead of reversed. This ensures a similar frequency

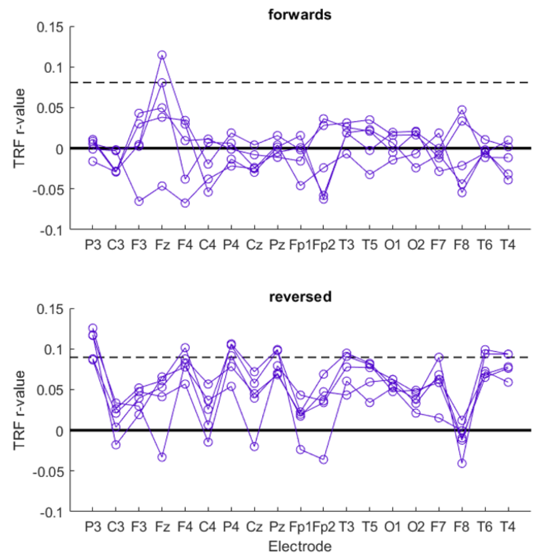

Fig. 5. r-values for each fold across the electrodes. The dotted line shows the 3σ value of the null distribution r-values.

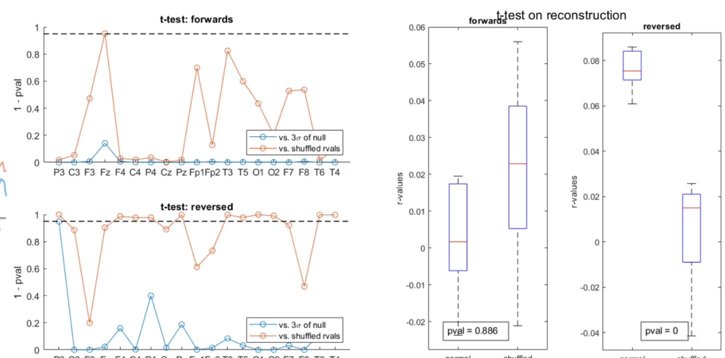

Fig. 6. t-test against null distribution for TRF as well as reconstruction r-values.

content in a more reliable manner, while maintaining a lack of general meaning.

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