EEG Beamformer Analysis and Optimization

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***Abstract*—The purpose of this paper is to analyze how beamforming techniques can be used to solve issues surrounding the process of measuring and processing electroencephalographic (EEG) data. This paper will begin by analyzing how beamforming is used to locate sources in EEG, and then examine what kinds of optimizations can be made to the process, specifically using beamforming in energy-constrained regions. Next, this paper will detail how eye-blink (EB) artifacts can be removed from EEGs using space-time-frequency-time/segment modeling (STF-TS) and robust minimum variance beamforming (RMVB).**

***Index Terms* – beamforming, electroencephalography (EEG), energy constrained regions, eye-blink (EB) artifact removal, robust minimum variance beamforming (RMVB), source localization, space-time-frequency-time/segment modeling (STF-TS)**

I. Introduction

Electroencephalography (EEG) measurements have been widely used in the process of determining how the brain functions. Compared to larger, more expensive methods of examination like magnetic resonance imaging (MRI) or positron emission tomography (PET), EEG measurements are cheap and easy to obtain. In addition, EEG measurements have improvements in temporal resolution compared to the aforementioned methods, and can provide information about neural activity on the scale of milliseconds as opposed to seconds or minutes. However, this higher temporal resolution is coupled with a lower spatial resolution – using EEG data may not tell you much spatially, i.e. where the signal sources are. Since the human brain is an incredibly complicated organ (or so it tells us) divided into different structures, we need to determine where the source is originating from to determine why it was generated in the first place.

Typically, these sources are modeled as a small number of equal dipoles and various algorithms are used to find the locations that minimize variance; however, this requires knowledge of how many sources there are in advance, and cannot be used when the sources are too close together. Beamforming techniques can be used to solve this problem by providing independent estimates of source activities. Yet, this does not perfectly solve our problem – most beamforming techniques will not perform well if the sources are close together, and will struggle when dealing with imperfect data.

EEG data can be corrupted by eye-blink (EB) artifacts, which occur when the patient blinks during the EEG measurement process. Blinking or moving one's eyes during this process will create electrooculogram (EOG) error data which is processed with the clean EEG data. EOG signals tend to have amplitudes an order of magnitude larger than EEG signals, and can last up to 300 milliseconds. This large corruption of data must be dealt with, or any beamforming algorithm will struggle to correctly identify the number and location of sources.

Although I do not personally have much experience in beamforming outside of my formal education, the methods it implements are easy to understand from a mathematical perspective. The topics we have learned in class so far will be imperative in the understanding of proper beamforming and the optimization of such a process.

I have chosen the following three papers to analyze: "*A Practical Guide to Beamformer Source Reconstruction for EEG*", written by Jessica J. Green and John J. McDonald, "*EEG Source Localization Using Beamforming in Energy-Constrained Regions*", written by D. Gutiérrez and C. C. Zaragoza-Martínez, and "*Removal of the Eye-Blink Artifacts from EEGs via STF-TS Modeling and Robust Minimum Variance Beamforming*", written by Kianoush Nazarpour, Yodchanan Wongsawat, Saeid Sanei, Jonathon A. Chambers, and Soontorn Oraintara. These papers detail the beamforming process, how it can be applied to EEG, what kinds of issues we will encounter, and how to solve them. I chose these papers because they build a solid understanding of using beamforming in EEG, expand upon that by detailing optimizations, and then touch upon errors and how to deal with them. I believe this will offer a broad coverage of the topic, while offering key insight into the technical details.

II. APPROACHES

The first paper, "*A Practical Guide to Beamforming Source Reconstruction for EEG"*, covers traditional methods of modeling EEG data, and then explains why beamforming can solve some of the issues associated with it. Before beamforming techniques were adapted for EEG usage, the neural sources of electrical fields, observed at the scalp by an array of sensors, were modeled by a specified number of equivalent dipoles. These dipoles are then positioned in the areas that exhibit the most variance depending on the number of dipoles specified. One could see that the initial issue of this method is that the number of dipoles must either be known or determined beforehand. This causes neural activity models generated from classical EEG analysis to be highly dependent on user input. In some situations, the number of dipoles may be accurately and easily approximated, allowing this method to work properly; however, in most situations the number of sources is not entirely clear.

This paper then expands upon the problems it brought to light, by offering a possible solution through beamforming. Beamforming is used in EEG to provide "independent estimates of source activities at multiple locations throughout the brain, resulting in a three-dimensional image of brain function" (Green). This avoids the inherent problem associated with dipole modeling, but does not come without its own set of limitations. A volume of space is set to represent the area inside the skull, and each point is evaluated as a beamformer. The result is a three-dimensional representation of source power throughout the brain. However, because dipoles vary in location and orientation, while the location may be fixed, the beamforming algorithm needs to determine the orientation. This is achieved through an iterative process that optimizes the dipole orientation over the selected time window. Linear beamformers can also be used, which instead use regional sources as opposed to dipole sources, which are approximated as three dipoles at orthogonal orientations to represent the *x, y*, and *z* planes. Both processes estimate source power throughout the specified volume to determine the source location(s).

The paper then begins to explain how using beamforming methods to resolve source locations can run into problems. The biggest drawback of using beamformers is the inability to localize correlated sources. The beamformer method assumes that source locations are not linearly correlated with any other source. Correlated sources are commonly found in common brain activities like attention and working memory.

Finally, the paper offers some solutions to combat the issues that arise from correlated sources. The first method proposed is to use a longer time window for imaging – because beamformer issues arise from temporal correlation, this allows more time for the correlations between source to diminish. The second proposed method explicitly accounts for any correlations in the beamforming algorithm itself. This can be accomplished when the locations of correlated sources are already known. This method can be used in conjunction with the traditional beamforming method to properly resolve correlated source locations.

The second paper, "*EEG Source Localization Using Beamforming in Energy-Constrained Regions*", expands upon the second method offered in the first paper. This process is typically performed over a specified region-of-interest (ROI), which "mitigates the cancellation effect of spatially separated yet covariant sources" (Gutierrez). It also makes the optimization problem less ill-posed and computationally faster. While using a ROI may minimize errors, it involves using anatomical constraints as well as a-priori knowledge of the correlated source locations. This problem is solved by using traditional beamforming techniques to estimate source locations, which are then used to explicitly define correlated locations. These locations are evaluated after explicitly defining their correlations, and the resulting correlated source locations should be made clear. This paper uses linearly constrained minimum variance (LCMV) beamforming and eigencanceling to perform accurate source decorrelation inside a ROI.

LCMV is attempting to solve the following problem:

$$\begin{aligned}&\underset{W(r_0)}{min}\ tr\{W^T(r_0)RW(r_0)\}\\&subject\ to\ W^T(r_0)A(r_0)=I\end{aligned} \tag{1}$$

Where tr{▪} is the trace of a matrix, $W(r_0)$ is the designed spatial filter, R is the data's covariance matrix, I is the identity matrix, and A is the array response matrix. This method is augmented using an eigencanceler, in which R^{-1} is replace by $\Pi\frac{1}{R}$, which is defined to be the projected matrix of the data onto the null space of the covariance matrix – this matrix is defined by:

$$\Pi\frac{1}{R}=U_0U_0^T \tag{2}$$

Where U_0 is the matrix whose columns are the eigenvectors of R that correspond to zero eigenvalues.

The ROI is defined in two steps: first the ROI is defined in the measurement domain based on the variability of the temporal data, and second the ROI is mapped to the source domain using a mapping rule. This rule is defined by projecting the measurement domain onto the source domain by an affinity transformation.

The work presented in the first two papers is a problem we have addressed in class, where two sources are spatially correlated. We have seen that traditional beamforming methods will not be able to resolve the individual sources if they are too close together without some optimizations. One method we saw that performed well was multiple signal classification (MUSIC). The MUSIC algorithm can be further optimized by performing recursively applied and projected MUSIC (RAP-MUSIC), or by performing first principle vectors (FINE).

The third and final paper, "*Removal of the Eye-Blink Artifacts from EEGs via STF-TS Modeling and Robust Minimum Variance Beamforming"*, strays away from the topic of general beamforming for EEG usage, and focuses more on the errors induced during the process. From the previous two papers, we have seen that many errors can arise from improperly specified correlations; however, larger sources of error can originate from eye-blink (EB) and eye movement artifacts. Smaller errors can be obtained during the process of placing the sensors on the patient's scalp, in which exact placement is subject to user error. Yet, EB errors tend to be an order of magnitude larger than the measurements themselves, so to maintain secure and accurate data, these issues must be handled primarily.

Spatial a-priori information is obtained by parallel factor analysis (PARAFAC) and plugged into a robust minimum variance beamformer (RMVB). This algorithm exploits the a-priori information as an estimation of the steering vector used to estimate the source location. This method does not require prior knowledge of what EB artifacts look like, or how electrooculogram (EOG) data will affect the EEG. Because this method is rather computationally expensive, the space-time-frequency (STF) signals are divided into time segments (TF), which allows for parallel PARAFAC to occur. The entire process can be summarized as:

(1) : bandpass filter the EEGs between 2 Hz and 30 Hz
(2) : set up the four-way array which contains the decomposition of the STF into segments, i.e. the STF-TF process
(3) : execute four-way PARAFAC using the four way array
(4) : exploit the spatial signature of the EB artifact and begin beamforming procedure
(5) : reconstruct the artifact-removed EEGs by deflation

This process is very mathematical and not very intuitive, but provided excellent results and properly filtered out EB artifacts from EEGs.

III. EVALUATION

The first paper showed that if the sources are only correlated for 40% of the time, extending the temporal window size will properly resolve the sources. This means that the EEG beamforming process does not need to be tweaked to such incredible detail as shown in the second and third papers. If our sources match this criterion, our computation will be fast and accurate if there are no other errors or artifacts present. This paper also showed that if the two sources are correlated, but located on different hemispheres of the brain, extending the temporal window will also lead to accurate source resolution. The volume that defines the region underneath the scalp must also be accurately tuned. If an incorrect model is used, the model will struggle to localize the sources. This paper did not actually perform a scientific experiment, but instead introduced the basics behind using beamforming to interpret EEG data, while explaining how those methods could be optimized.

While the results of this paper did not contribute to the advancement of EEG or beamforming since it took a more explanatory approach, the ramifications from it are very useful in the professional and academic settings. Beamforming is rather complex subject, and while there may be many resources available on the topic, most are mathematically dense. This paper presents the beamforming method intuitively, and highlights issues that would be otherwise hard to notice. The ground established in this paper allows other research to build off it, and can be used as a stepping stone to further, more applicable research.

The second paper obtained good results, but did not account for variations in head shape. As found in the first paper, variations or improper modeling of the head volume can create errors and other artifacts. However, using LCMV to determine the ROI, and then using eigencancelers within the ROI to more accurately determine source locations. Figure 1 on the next page shows the results of using LCMV. Although it may be hard to see, the image above clearly identifies the location of a source. Next, the eigencanceler is applied to the ROI, and the location of the sources is determined. Figure 2 on the next page shows the results of using the eigencanceler. Yet again, it may be hard to see, but individual locations are highlighted near the specified ROI, and a higher level of resolution is present. Overall, the process reduced the computational cost of the process compared to an exhaustive search over the entire brain area.

The results offered from this paper are very applicable to real-world implementations, as it can provide further analysis of EEGs accurately, while still being simple enough to implement. This means that EEG data can be computed at a much faster rate than

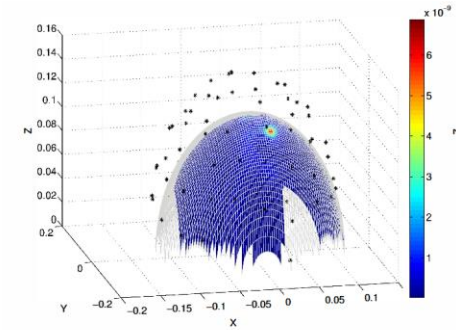

Fig.1: Result of using LCMV to estimate source location and consequently the ROI

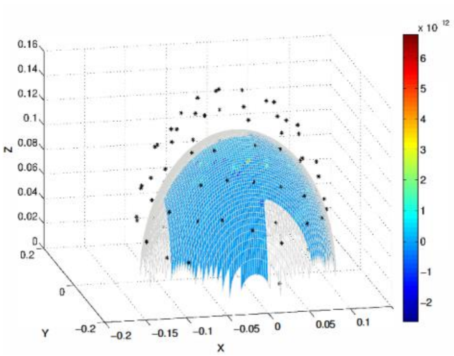

Fig.2: Result of using eigencanceling to determine source location within the ROI

classical EEG analysis, offering faster and more accurate diagnoses. Although EEG data carries less weight in the scientific fields due to the many problems it has, the slow and steady process of resolving those issues may lead to a more widespread usage of EEG, as well as research into using EEGs to properly diagnose diseases.

The third paper had very good results, and could remove EB artifacts, perform reconstruction, and still be computationally cheap. EB artifacts are represented as large spikes when EEG data is plotted as a time signal. Figure 3 shows how EB artifacts can ruin EEG data, and Figure 4 shows the results of using four-way PARAFAC, along with beamforming techniques, to remove those EB artifacts and preserve the raw EEG data.

These results are incredibly applicable to many real-world scenarios involving EEGs, and solves one of the major issues associated with EEG. The removal of EB artifacts can allow beamforming algorithms to make more accurate estimates of source locations while preventing false sources from arising. These developments, along with the developments made in the second paper, can be used to raise EEGs scientific prowess. As the reputation of using EEGs to diagnose disease increases, more research can be focused into adapting EEG research into other areas. As the EEG process becomes more refined, it becomes more useful to doctors and healthcare professionals.

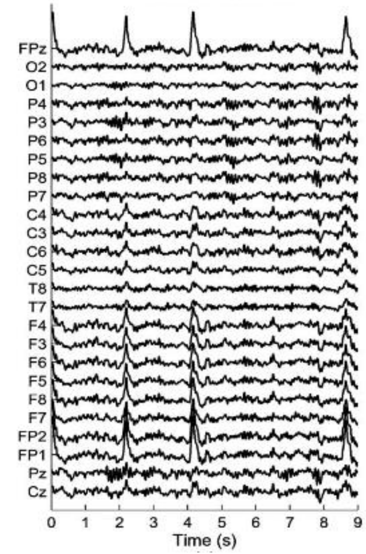

Fig.3: Plot of an EEG signal that has been corrupted by EB artifacts.

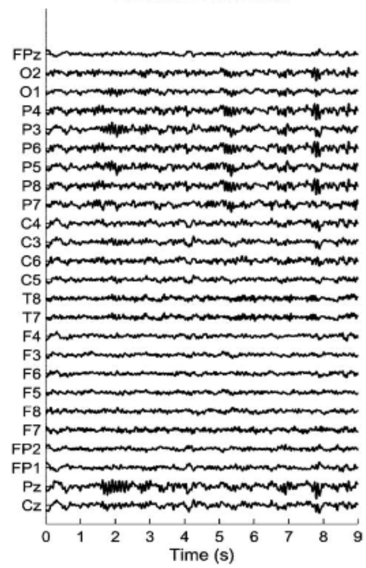

Fig.4: Result of applying four-way PARAFAC, beamforming, and reconstruction via inflation to the EB-artifact-contaminated EEG data in Figure 3

IV. Discussion

The first paper summarizes how to use beamforming techniques to resolve source localization problems in EEG, along with some of the problems it can encounter. The paper presents three main advantages of using beamformers to resolve source locations:

(1) : the beamformer method does not require a-priori knowledge of the number of sources.

(2) : the beamformer method is able to focus source localization on specific frequency bands.

(3) : the beamformer method finds estimates at each location, and avoids solving an inverse problem, which may be computationally expensive.

The evidence provided in this paper clearly shows that beamforming should be an important aspect of EEG analysis, even though it may have its limitations. Using traditional dipole modeling methods will lead to biased data since the number of dipoles must be set manually. By using beamforming techniques, we can avoid these biasing issues.

The results shown from the second paper showed that performing eigencanceling on a pre-determined ROI can provide more resolution when determining source locations. Compared to the traditional beamforming techniques described in the first paper, using a ROI can offer a more focused and less biased source location estimation. As you can see from Figures 1 and 2, in this example, traditional LCMV beamforming will find one strong source. When this source location is set as the ROI, and eigencanceling is applied, we can see the presence of many smaller sources. LCMV combines these sources into one larger one, whereas eigencanceling allows these sources to become present due to a higher resolution. However, this example uses a generic head shape to approximate locations – head shape varies from person to person, and if the exact locations of the sources is required, then we must also accommodate for changes in head geometry.

The third paper offered some astounding results. The amount of corruption EB artifacts introduced into EEG data was very large, which can have significant effects on the source location estimation process. We can clearly see from Figures 3 and 4 how their algorithm removed EB artifacts from the EEG data, and did an excellent job of reconstructing the underlying signal. However, their method did have a few issues. Because EB artifacts can vary in terms of their amplitude and how they affect the different channels, a large number of steering vectors will need to be generated. The variability of this set of steering vectors could make learning difficult depending on the nature of EB artifacts. EB artifacts are not the only types of EOG contamination present in EEG – eye movements and saccade artifacts will still be present in the signal after this being processed by this algorithm. While their errors are not as significant as those associated with EB artifacts, we would like to mitigate as much error as possible.

V. Conclusions

After reading through these papers, I have come to understand in detail how we can use beamforming techniques to resolve source locations in EEG. Beginning with the first paper, we are introduced to general beamforming and the types of problems associated with it. Because beamforming can be a rather technical topic, this paper is a great introduction to the ideas behind the strategy. The second paper expands upon the first by answering some of the issues it posed – specifically regarding spatially correlated sources. It has been shown that we can use traditional beamforming to determine a ROI, and then use eigencanceling to further analyze this area. The results will have significantly higher resolution, and many spatially correlated sources that would be masked in traditional beamforming become visible. The third paper introduces a new issue to address, which is the removal of EB artifacts. I chose this article because it presents a very real problem, and solves it in a complex, yet intuitive manner. The results of this paper show that we can use four-way PARAFAC to remove EB artifacts, and encourage clean EEG data.

I believe these papers can offer valuable insight in both an introductory and technical manner. They explain the topic, introduce issues, offer some solutions, and then explain a real-world example.

VI. References

Green, Jessica J., and John J. McDonald. "A Practical Guide to Beamformer Source Reconstruction for EEG." Ed. Todd C. Handy. *Brain Signal Analysis: Advances in Neuroelectric and Neuromagnetic Method* (2009): 79-98. Web.

Gutierrez, D., and C. C. Zaragoza-Martinez. "EEG Source Localization Using Beamforming in Energy-Constrained Regions." (n.d.): 1-4. *IEEEXplore*. Web.

Nazarpour, Kianoush, Yodchanan Wongsawat, Saeid Sanei, Jonathan A. Chambers, and Soontorn Oraintara. "Removal of the Eye-Blink Artifacts From EEGs via STF-TF Modeling and Robust Minimum Variance Beamforming." (n.d.): 1-11. *IEEEXplore*. Web.