BCIs: Improving Spatial Resolution and Spatial Filtering Algorithms

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Topics in Bioengineering

1 Abstract

BCI's utilize our brain signals to translate our thoughts into the real world. They have many applications including medical devices, prevention, diagnosis, video games, and even modular environments that adapt to one's mood. Non-invasive signal acquisition methods are more common, as surgery isn't required, with the most popular one being the electroencephalogram (EEG). EEGs have great theoretical temporal resolution, but improving their spatial resolution is a point of improvement. Unfortunately, the theoretical temporal resolution of BCI's is being lowered due to having a lower spatial resolution. In addition to this, there are quite a few artifacts that can skew the signal of the EEG. A few examples of this are tongue, eye, and muscle movement. In order to improve signal quality, spatial resolution needs to increase and artifacts need to be removed from the signal in what is called the preprocessing stage. This paper will discuss various ways of increasing spatial resolution and introduce a few important spatial resolution algorithms.

2 Introduction

Brain computer interfaces (BCI) are systems which interpret brain signals into intention which can then be actualized in the external world. This could be moving a limb, speaking, or even something as abstract as paying attention to an advertisement on television. BCI technology began mostly in the biomedical space, specifically with helping people who have mobility or speaking problems.[1] An example of an early BCI research project was figuring out the best algorithm to convert brain signals to the direction and movement of a cursor in two dimensions.[8] The majority of BCI research still has to do with creating new medical solutions and technologies.

A lot of useful information about a person's mood, attentiveness, and sleep state can also be found from signals acquired from the brain.[1] BCIs that utilize this sort of information to drive their technologies are called passive BCIs.[1] There has been a recent surge of passive BCI technology development in the medical area. For example, user state monitoring by analyzing brain signals with regards to motion sickness has a lot of applications in preventing traffic accidents as it has been implicated in causing them.[9] Other examples of passive BCI technologies being developed in similar areas are the diagnoses of seizure disorders, tumors, dyslexia, dyskinesia, peripheral neuropathy, and other musculoskeletal diseases.[1]

BCI technologies are also being developed for a larger consumer base. Smart environments are being developed that adapt to suit one's mood.[1] Marketing companies are using BCI technology to track attention to their advertisements.[1] In addition to these, combining traditional video game environments with brain controlling capabilities is a point of interest for entertainment companies.[1] Lastly, utilizing the fact that brain signals can be used as a unique identifier, security systems that use BCI technologies are being developed (refer to figure 1 for more information regarding BCI research areas).[1] As BCI algorithms made for the mass consumer market need to accumulate brain signal data from a lot of people in various states, the ethical implications and problems that arise with storing and using such a large amount of clinical data are being studied.

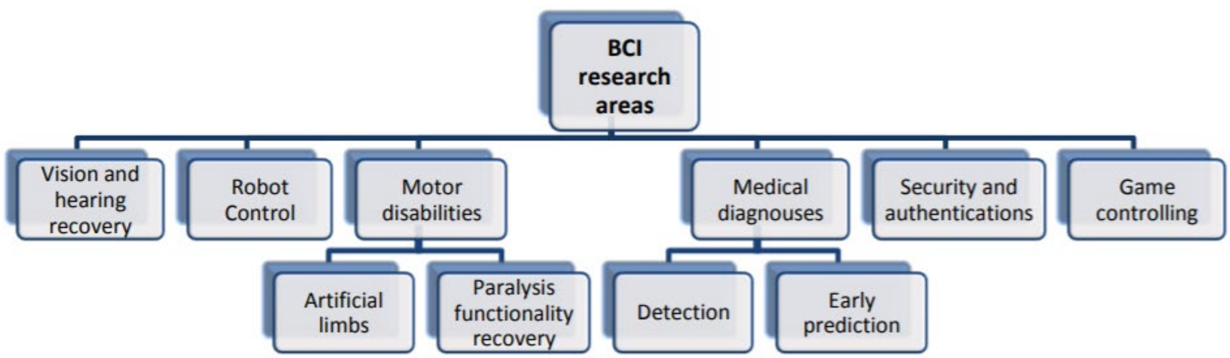

Figure 1: This is a full visual explanation of all of the areas that BCI technology is being researched today.[3]

The whole BCI system, from getting the signal from the brain to obtaining meaning from it, has four stages: signal acquisition, signal preprocessing, feature extraction, and classification.[1] Signal acquisition describes the stage at which the brain waves are being recorded.[1] Signal preprocessing removes a lot of the artifacts and noise that are recorded.[1] Feature extraction identifies and distinguishes the parts of the signal that are of interest which allows the signal to be more easily understood.[1] This also decreases the size of the data that needs to be classified.[1] Lastly, the classification stage involves grouping the output of the feature extraction stage into actionable device commands in the BCI system.[1] For example, with regards to the two-dimensional cursor movement study, the signal could be classified into direction or speed. In the case of a passive BCI system like the motion sickness study described earlier, the signal could be grouped into different levels of motion sickness.

There are many ways to acquire signals from a brain. At the higher level, there are invasive and non-invasive signal acquisition methods.[1] Invasive methods are usually implanted in a patient's brain or on the surface of the brain.[1] Therefore, there are a lot of areas that could potentially lead to failure. Biocompatibility of the implants is a huge challenge as the body can easily reject the implant due to an immune response.[2] In addition, the functionality of the implant deteriorates over time and the implant cannot be replaced easily as it requires surgery. To make matters worse, they are large enough to cause tissue damage which can lead to implant failure.[2] As invasive methods also require brain surgery and the risk isn't worth the benefit unless someone is immobilized or unable to communicate, non-invasive methods are used for research with more subjects. In this paper, we will be discussing the electroencephalogram (EEG) as our primary method of signal acquisition (refer to figure 2 for an image of an EEG).

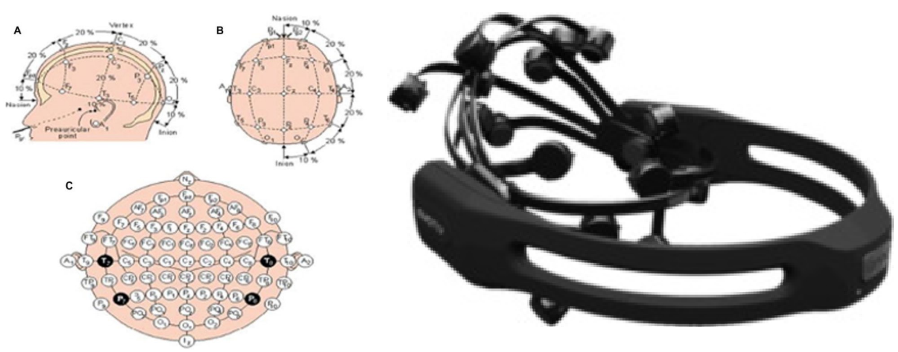

Figure 2: (left) This is an image showing position of how an EEG is placed and how information from some electrodes can be monitored separately to understand different parts of the brain.[1] (right) This is a modern, portable, and cheap EEG.[1]

EEGs are a non-invasive method of signal acquisition for BCIs and are very portable and relatively easy to place.[1] As a result, they are the best signal acquisition method for commercially available BCI systems to use. They utilize electrodes on different parts of the scalp to record voltage fluctuation in order to look at neural activity thousands of times per second *(refer to figure 2)*.[1] In a more general sense, various locations of the brain are more and less active dependent on the activity that is being carried out. Therefore, if the area of interest in the brain in known, the electrodes can be placed on the corresponding section of the scalp in order to record that information.

There are a lot of artifacts that can contaminate the brain signal when it is being recorded.[3] Human variation in electrode placement can cause inconsistencies in signal acquisition between sessions. This is more of an issue while using an EEG because the placement of the electrodes changes every time in comparison to an implant where this is not the case. Incorrect placement of the electrodes can also potentially create more artifacts.[3] There are also a lot of physiological artifacts that the EEG picks up.[3] Internal movement also distorts the signal: eye movement, pulse, heart beating, tongue movement, and random muscle movement.[3] Removal of the artifacts during the preprocessing stage allows for a clearer signal where the features of interest can be more easily identified during the feature extraction stage.

A downside to BCI technology is the large training time in order for a user to get used to the system.[1] Controlling something with your brain requires a lot of time to perfect and improve at. This can sometimes be weeks of steady training. In addition to this, the brain is a non-linear system and its signals have a high dimensionality.[1] They have a high dimensionality because the signals are preserved to keep spatial accuracy (refer to figure 3 to visually see the complexity of an EEG recording).[1] Feature extraction can help reduce the dimensionality as, at this stage, only the most important data is retained. This is why it is so critical to remove artifacts of signal acquisition as accurately as possible before.

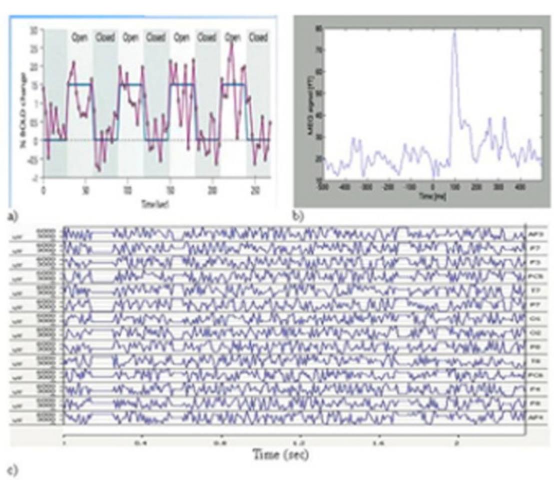

Figure 3: (Top Left) Blood-Oxygen-Level-Dependent Changes, (Top Right) Magnetic Signals Recorded From the Brain, (Bottom) Electrical Signals Recorded From The Brain; All of these show the complexity of the data that is recorded from an EEG.[1]

3 Temporal and Spatial Resolution

The downsides to using an EEG is that there is a small signal to noise ratio.[3] EEGs fall into the electrophysical category of non-invasive brain imaging techniques which are considered to have good temporal resolution and poor spatial resolution.[4] Higher spatial resolution means that the information we know regarding the originating location of the signal can be more precisely found.[5] With EEGs, there is a lower spatial resolution because the electrical signal travels through the skull which has low conductivity.[5] This makes it harder to tell where exactly the signal is from. In addition, when a neuron fires, a dipole is formed from the synapses to the axon.[5] An electric charge is then carried down the axon and the neuron “fires”. When just one neuron fires, it isn’t enough for the EEG to measure, so the EEG can only really look at clusters of neurons that are about the size of a dime firing.[5] The amount of neurons in a dime sized cluster is astronomically large.[4,5] In addition, signals from nearby regions are also picked up by the electrode which alters the information gathered.[4,5] Therefore, the facts that the skull has a low conductivity, EEGs require a large amount of neurons to fire at the same time, and nearby signals interfere with the desired location cause lowered spatial resolution. To improve spatial resolution, using up to 256 electrodes was proposed.[1] In addition, the 10-20 system to positioning electrodes was published.[6] This is a system that is used to describe the location of the nineteen electrodes used initially using placement at 10%-20% of the radius of the scalp.[6]

On the other hand, EEGs have great temporal resolution. This means that they are able to track the electrical signals many times a second at each sensor.[5] Some argue that EEGs temporal resolution isn’t as great as we think it is because the electrodes are more phase locked which causes more coherence between sites that is actually the case.[4]

Spatial and temporal resolutions are generally considered to be independent from one another, meaning that one does not affect the other.[4] But they can be argued to be interdependent, meaning that without decent spatial resolution, it is impossible to have a temporal resolution as great as the theoretical one.[4] To prove this point, it is known that computing the Surface Laplacian of the scalp potential data improves the spatial resolution of EEGs as it is a spatial filter.[4] The algorithm subtracts the average neighboring electrode activity from the electrode in question.[7] It creates a local relationship between general brain activity and the activity of interest which removes random surges in brain signal due to nearby ones.[7] Burle et al. shows that computing the

Surface Laplacian of the scalp potential data improves both temporal resolution and spatial resolution.[4] Since both are positively impacted by the Surface Laplacian filter, when spatial resolution is lower, temporal resolution is also lower. This means that the theoretical temporal resolution that EEGs are able to reach isn't being accomplished.[4] To solve this problem, using spatial filters in the preprocessing algorithm is required.

4 Other Spatial Filtering Algorithms

A spatial filtering method that is a common thread between many BCI research projects is Independent Component Analysis, or ICA.[1] It heavily improves signal to noise ratio by decomposing the received signal into brain activities and non-neural activities like the muscle movement artifacts discussed earlier.[10] The idea behind ICA is to try to find the linear projections of the data that maximizes their independence from one another.[10] This is essentially finding the parts of the signal that are the most different from one another. As a result, ICA is very good at separating the signal into components that originate from different sources. For example, after applying ICA, it can sort the signal into spatial origination and into different artifacts like eye movements, muscle contractions, and tongue movement.[10]

ICA works by assuming that there are n-channels from the scalp EEG such that when the source signals from the EEG, 'S', are weighted by 'A', a n×n mixing matrix that predicts that certain electrodes have different weights, the EEG data results, 'X' (refer to equation 1).[10,11] Once 'X' is found, the recovered source signals, 'U', can be found by applying an unmixing matrix 'W' of m×n dimension, where 'm' is the number of independent sources (refer to equation 2).[10]

$$X = A \cdot S$$

Equation 1: This is the equation where a linear combination of the independent sources 'S', weighted by the mixing matrix 'A', is equal to the data 'X'.

$$U = W \cdot X$$

Equation 2: This equation describes 'X' weighted by the unmixing matrix W which equals to the matrix 'U', the recovered source signals after ICA is performed. W^{-1} holds the weights that the electrodes individually have.[10]

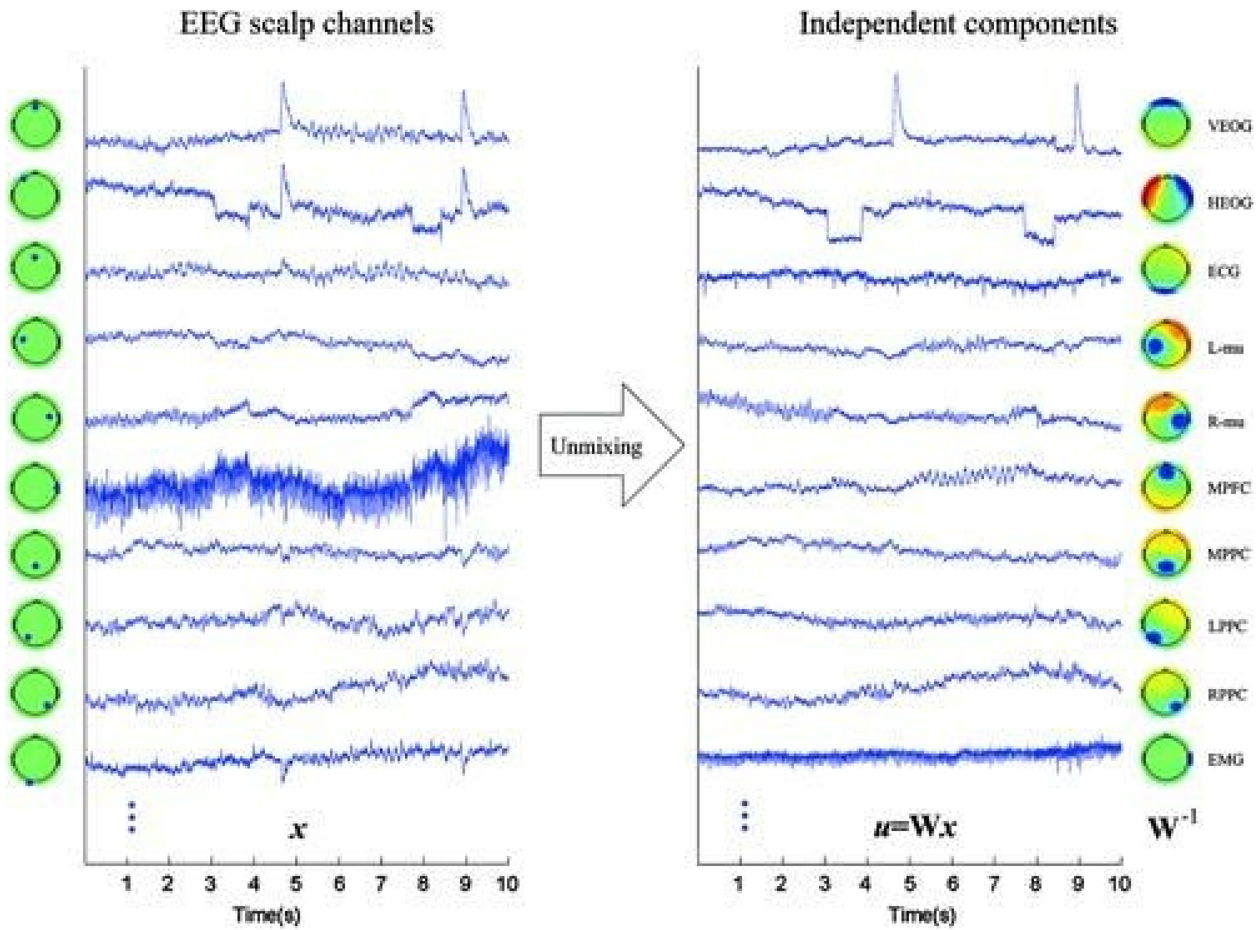

Figure 4: This is a visual representation of how ICA performs. The columns of W^{-1} are shown visually through the scalp maps. The scalp maps on the left side show the initial origin electrode of the data and the scalp maps on the right side show what electrodes ICA weighted more heavily. The general weighting points to ICA being very good at recognizing the spatial location of the signal in question. [10]

A more specific spatial filtering algorithm is the Common Spatial Pattern algorithm, or CSP.[12] This algorithm is most often used classifying 2-class motor imagery EEG data.[12] Motor imagery involves thinking about motion and trying to recreate it using BCI technology. Examples of this include the two-dimensional cursor movement study described earlier. The biggest problem with motor-imagery based BCI is that there is a lot of variability between subjects.[12] In order to use CSP, the interval of frequencies of interest, or the band-pass filter values, and the time range of interest need to be specified, therefore resulting in epoched EEG trials.[11,12] (For reference, epoched data is when time windows of interest are extracted from the complete EEG signal. Usually these time windows correspond with a specific stimulus.) The essential idea behind CSP is to separate the EEG into subcomponents that have the most variance between them, or, in other words, separate things by the ones that are the most different.[11]

The Laplacian filter is one of the simpler spatial filtering algorithms and was used to prove that temporal and spatial resolution are related (refer to equation 3).[4] There is also the Common Average Reference filter subtracts the average potentials of all the channels from each channel, similar to the Laplacian filter.[13] This algorithm does not favor or highlight any electrodes as ICA does, and gets rid of the DC bias of the spatial frequency spectrum *(refer to equation 4)*.[13] DC bias is the offset of the signal. In other words, the DC bias will be zero if the mean amplitude is zero. In a paper written by Allonso et al., the accuracy of spatial filters were tested by using the same classification and feature extraction algorithm while changing the spatial filtering algorithm.[13] The Laplacian filter correctly classified user choice an average of 81.5%, while the Common Average Reference had the second highest of 79%.[13] These accuracies were testing with four different users with many tests with each individual subject.[13]

$$e_i^{Laplace}(t) = e_i(t) - \frac{1}{K}\sum_j^K e_j(t)$$

Equation 3: This is the equation for the Laplacian filter where i symbolized the ith electrode and j is the index of the neighboring electrodes, and K is 4 because the electrodes selected are the ones in a 'plus' formation around the ith electrode.[13]

$$e_i^{CAR}(t) = e_i(t) - \frac{1}{N}\sum_j^N e_j(t)$$

Equation 4: This is the equation which describes how the common average reference is calculated.[13]

5 Discussion

Improving spatial resolution accuracy is incredibly important as it isn't allowing EEGs to reach their theoretical temporal resolution which will allow them to record voltage fluctuations thousands of times per second. This amazing temporal resolution is one of the reasons one might use an EEG. Spatial filtering algorithms play an integral role in increasing the spatial resolution in conjunction with placing electrodes in the 10-20 orientation and using up to 256 electrodes. ICA proves to be incredibly useful as it can do both feature extraction and spatial filtering. Using ICA in combination with other algorithms as needed with regards to the purpose of the BCI tool can be beneficial to the spatial resolution of the signal as well. For example, CSP was discussed as having relevance in the motor-imagery space. There are also many more spatial filters like the Spatial Smoothing Filter, Weighted Average Filter, among others that are constantly being tested and analyzed very regularly as the BCI space is still mostly in the research stage. Questions like these are what is keeping a lot of medical devices, or consumer products from becoming commercially available. There is always room for improvement and further experimentation with combinations of spatial-resolution-improving algorithms, other preprocessing and feature extraction algorithms, and feature classification algorithms. There needs to be better documentation regarding different spatial filtering algorithms, their uses, accuracies, other algorithms with which they are commonly used with and uses of BCIs in which they function better. They should be documented such that there is a simpler way of finding a starting place for medical device and other BCI product companies to create working algorithms which can potentially lead to more commercially available BCI systems.

6 Endnotes

[1] Abdulkader, Sarah N., Ayman Atia, and Mostafa-Sami M. Mostafa. "Brain Computer Interfacing: Applications and Challenges." *Egyptian Informatics Journal* 16, no. 2 (July 1, 2015): 213–30. https://doi.org/10.1016/j.eij.2015.06.002.

[2] Waldert, Stephan. "Invasive vs. Non-Invasive Neuronal Signals for Brain-Machine Interfaces: Will One Prevail?" *Frontiers in Neuroscience* 10 (June 27, 2016). https://doi.org/10.3389/fnins.2016.00295.

[3] Nelly Elsayed, "Brain Computer Interface: EEG Signal Preprocessing Issues and Solutions," 2017, https://doi.org/10.5120/ijca2017914621.

[4] Borís Burle et al., "Spatial and Temporal Resolutions of EEG: Is It Really Black and White? A Scalp Current Density View," *International Journal of Psychophysiology* 97, no. 3 (September 2015): 210–20, https://doi.org/10.1016/j.ijpsycho.2015.05.004.

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[6] Charline Hondrou and George Caridakis, "Affective, Natural Interaction Using EEG: Sensors, Application and Future Directions," 2012, 331–38, https://doi.org/10.1007/978-3-642-30448-4_42.

[7] Claudio Carvalhaes and J. Acacio de Barros, "The Surface Laplacian Technique in EEG: Theory and Methods," *International Journal of Psychophysiology*, On the benefits of using surface Laplacian (current source density) methodology in electrophysiology, 97, no. 3 (September 1, 2015): 174–88, https://doi.org/10.1016/j.ijpsycho.2015.04.023.

[8] Jonathan R. Wolpaw and Dennis J. McFarland, "Control of a Two-Dimensional Movement Signal by a Noninvasive Brain-Computer Interface in Humans," *Proceedings of the National Academy of Sciences of the United States of America* 101, no. 51 (December 21, 2004): 17849–54, https://doi.org/10.1073/pnas.0403504101.

[9] L. Ko et al., "EEG-Based Motion Sickness Classification System with Genetic Feature Selection," in *2013 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)*, 2013, 158–64, https://doi.org/10.1109/CCMB.2013.6609180.

[10] Yijun Wang and Tzyy-Ping Jung, "Improving Brain–Computer Interfaces Using Independent Component Analysis," in *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*, ed. Brendan Z. Allison et al., Biological and Medical Physics, Biomedical Engineering (Berlin, Heidelberg: Springer Berlin Heidelberg, 2013), 67–83, https://doi.org/10.1007/978-3-642-29746-5_4.

[11] Dongrui Wu et al., "Spatial Filtering for EEG-Based Regression Problems in Brain-Computer Interface (BCI)," *ArXiv:1702.02914 [Cs]*, February 9, 2017, http://arxiv.org/abs/1702.02914.

[12] Kai Keng Ang et al., "Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b," *Frontiers in Neuroscience* 6 (2012), https://doi.org/10.3389/fnins.2012.00039.

[13] D. R. Alonso and M. M. B. R. Vellasco, "Spatial Filter Comparison for a Brain Computer Interface," in *2016 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, 2016, 1–6, https://doi.org/10.1109/LA-CCI.2016.7885718.

7 Bibliography

Abdulkader, Sarah N., Ayman Atia, and Mostafa-Sami M. Mostafa. "Brain Computer Interfacing: Applications and Challenges." *Egyptian Informatics Journal* 16, no. 2 (July 1, 2015): 213–30. https://doi.org/10.1016/j.eij.2015.06.002.

Abdulkader et al. cover a wide range of topics with regards to BCI's. They begin with applications, go over the four stages of BCIs, and finish with the reasons BCIs are still undergoing lots of research to this day.

Waldert, Stephan. "Invasive vs. Non-Invasive Neuronal Signals for Brain-Machine Interfaces: Will One Prevail?" *Frontiers in Neuroscience* 10 (June 27, 2016). https://doi.org/10.3389/fnins.2016.00295.

Waldert talks about the types of signal acquisition methods for BCIs. He talks about the pros and cons of invasive and non-invasive BCI's.

Nelly Elsayed, "Brain Computer Interface: EEG Signal Preprocessing Issues and Solutions," 2017, https://doi.org/10.5120/ijca2017914621.

This article covers the types of artifacts that occur when using an EEG as a signal acquisition method and why they occur. It also talks about the different preprocessing methods to get rid of these artifacts.

Borís Burle et al., "Spatial and Temporal Resolutions of EEG: Is It Really Black and White? A Scalp Current Density View," *International Journal of Psychophysiology* 97, no. 3 (September 2015): 210–20, https://doi.org/10.1016/j.ijpsycho.2015.05.004.

Borís et al. show that temporal and spatial resolutions really aren't completely independent. They use the Surface Laplacian algorithm to do this.

"Intro to Brain Computer Interface," NeurotechEDU, accessed May 2, 2019, http://learn.neurotechedu.com/introtobci/.

This article provides a good introduction to a lot of the language and jargon surrounding BCIs. It also talks about the science behind the signal acquisition methods.

Charline Hondrou and George Caridakis, "Affective, Natural Interaction Using EEG: Sensors, Application and Future Directions," 2012, 331–38, https://doi.org/10.1007/978-3-642-30448-4_42.

This artcle talks about the different aspects of using an EEG in signal acquisition. It touches on feature extraction and machine learning algorithms.

Claudio Carvalhaes and J. Acacio de Barros, "The Surface Laplacian Technique in EEG: Theory and Methods," *International Journal of Psychophysiology*, On the benefits of using surface Laplacian (current source density) methodology in electrophysiology, 97, no. 3 (September 1, 2015): 174–88, https://doi.org/10.1016/j.ijpsycho.2015.04.023.

Carvalhaes et al. talk about the surface laplacian method. They explain the algorithms perks and the math surrounding it.

Jonathan R. Wolpaw and Dennis J. McFarland, "Control of a Two-Dimensional Movement Signal by a Noninvasive Brain-Computer Interface in Humans," *Proceedings of the National Academy of Sciences of the United States of America* 101, no. 51 (December 21, 2004): 17849–54, https://doi.org/10.1073/pnas.0403504101.

This study looked at people controlling a cursor in two-dimensions using BCI's. The sample size of test subjects was small and the time commitment with regards to training to use the BCI can be seen clearly.

L. Ko et al., "EEG-Based Motion Sickness Classification System with Genetic Feature Selection," in *2013 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)*, 2013, 158–64, https://doi.org/10.1109/CCMB.2013.6609180.

Ko et al. talked about how using passive BCI technology to track motion sickness could ultimately help stop car accidents. They used genetic feature selection to do this.

Yijun Wang and Tzyy-Ping Jung, "Improving Brain–Computer Interfaces Using Independent Component Analysis," in *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*, ed. Brendan Z. Allison et al., Biological and Medical Physics, Biomedical Engineering (Berlin, Heidelberg: Springer Berlin Heidelberg, 2013), 67–83, https://doi.org/10.1007/978-3-642-29746-5_4.

This paper provided a good introduction as to what ICA was and how the algorithm worked. Good figures and explanations of how different spatial filters were used through different research projects were shown.

Dongrui Wu et al., "Spatial Filtering for EEG-Based Regression Problems in Brain-Computer Interface (BCI)," *ArXiv:1702.02914 [Cs]*, February 9, 2017, http://arxiv.org/abs/1702.02914.

Wu et al. talked about many different spatial filtering algorithms and explained them all mathematically. They propose two CSP filters that use fuzzy sets.

Kai Keng Ang et al., "Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b," *Frontiers in Neuroscience* 6 (2012), https://doi.org/10.3389/fnins.2012.00039.

This paper talks about the FBCSP algorithm which was an iteration on the CSP algorithm. They explained the OVP CSP algorithm among other variations.

D. R. Alonso and M. M. B. R. Vellasco, “Spatial Filter Comparison for a Brain Computer Interface,” in *2016 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, 2016, 1–6, https://doi.org/10.1109/LA-CCI.2016.7885718.

This paper compares different spatial filters that are commonly used. A comprehensive table talking about accuracies for different algorithms is given.

“(PDF) Recent Advances in Brain-Computer Interfaces,” ResearchGate, accessed March 28, 2019, https://www.researchgate.net/publication/37452383_Recent_Advances_in_Brain-Computer_Interfaces.

This paper provides a comprehensive look at all of the stages of BCI signal acquisition and processing. An example of a BCI system is also provided and the results are discussed.

Paul Hammon, “Preprocessing and Meta-Classification for Brain-Computer Interfaces,” accessed April 18, 2019, http://www.cogsci.ucsd.edu/academicPubs/desa/ieeetransbme.pdf.

Hammon covers the different stages of preprocessing in a comprehensive table. This paper looks at combining multiple classifiers to improve classification for single classifiers.