Analysis of Processing Methods Citations

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Annotated Citation List:

[1] H. Lu, H. Eng, C. Guan, K. N. Plataniotis and A. N. Venetsanopoulos, "Regularized Common Spatial Pattern With Aggregation for EEG Classification in Small-Sample Setting," in IEEE Transactions on Biomedical Engineering, vol. 57, no. 12, pp. 2936-2946, Dec. 2010, doi: 10.1109/TBME.2010.2082540.
https://ieeexplore-ieee-org.ezproxy.proxy.library.oregonstate.edu/document/5593203

> This paper compares the results of the R-CSP-A algorithm to other variations of CSP and concludes that R-CSP-A is an effective algorithm to use with EEG data.

[2] S. Park, D. Lee and S. Lee, "Filter Bank Regularized Common Spatial Pattern Ensemble for Small Sample Motor Imagery Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 26, no. 2, pp. 498-505, Feb. 2018, doi: 10.1109/TNSRE.2017.2757519.
https://ieeexplore-ieee-org.ezproxy.proxy.library.oregonstate.edu/document/8052556

> This 2018 paper explores the benefits of regularization with CSP and concludes that it is a beneficial addition for feature extraction.

[3] Yao Guo, Yuan Zhang, Zhiqiang Chen, Yi Liu, Wei Chen, EEG classification by filter band component regularized common spatial pattern for motor imagery, Biomedical Signal Processing and Control, Volume 59, 2020, 101917, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2020.101917.
http://www.sciencedirect.com/science/article/pii/S1746809420300732

> Another paper discusses how to improve upon the basic CSP algorithm to optimize feature generation. This 2020 paper focuses on filter band component regularized CSP and shows results that this method produces higher accuracy for most subjects.

[4] V. Mishuhina and X. Jiang, "Feature Weighting and Regularization of Common Spatial Patterns in EEG-Based Motor Imagery BCI," in IEEE Signal Processing Letters, vol. 25, no. 6, pp. 783-787, June 2018, doi: 10.1109/LSP.2018.2823683.
https://ieeexplore-ieeeorg.ezproxy.proxy.library.oregonstate.edu/document/8331858

> This paper specifically touches on the drawbacks of CSP and why regularization and other aiding methods are needed to be successful. This 2018 paper addresses methods that can be used to alleviate the problems of overfitting and inaccurate generalization that tend to come with CSP.

[5] M. Krauledat, G. Dornhege, B. Blankertz, F. Losch, G. Curio and K. -. Muller, "Improving speed and accuracy of brain-computer interfaces using readiness potential features," The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, CA, 2004, pp. 4511-4515, doi: 10.1109/IEMBS.2004.1404253.
https://ieeexplore-ieeeorg.ezproxy.proxy.library.oregonstate.edu/document/1404253

> This paper discusses CSP as a filtering method and emphasizes its value in rapid response systems which is applicable for our purposes.

[6] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," in Proceedings of the IEEE, vol. 89, no. 7, pp. 1123-1134, July 2001, doi: 10.1109/5.939829. https://ieeexplore-ieee-org.ezproxy.proxy.library.oregonstate.edu/document/939829

This paper walks through the basic implementation of CSP and describes the mathematical steps taken to produce the projection matrix.

[7] K. Liao, R. Xiao, J. Gonzalez, and L. Ding, “Decoding individual finger movements from one hand using human EEG signals,” PloS one, 08-Jan-2014. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3885680/. [Accessed: 21-Jan-2021].

This paper compares EoG (implanted in scalp, more accurate) and EEG (gathered from scalp, more volatile and less accurate) data. It specifically argues that EEG data can be decoded and applied to classify finger movements to attain an accuracy of 77.11%. Here are the highlights of the paper:

- All gathered data from this experiment was from 11 healthy right-handed participants.
- A high pass filter was applied to the EEG data at .3Hz and a notch filter was applied to eliminate power line noise at 60Hz.
- ICA was also applied to the data to examine EEG specific data without the additional noise.
- Finger movement was band-pass filtered between 0.5-2Hz to eliminate outside noise.
- Power spectral density is then applied to the data to analyze particular frequency bands.
- Principal component analysis is then applied to the PSD algorithm to highlight the most volatile features.
- A five-fold cross validation was applied to the data using an SVM machine learning model.

[8] Siuly, S., & Li, Y. (2015, January 30). Designing a robust feature extraction method based on optimum allocation and principal component analysis for epileptic EEG signal classification. Retrieved April 27, 2021, from https://www.sciencedirect.com/science/article/abs/pii/S0169260715000206

This paper focused on classifying cases of epilepsy vs. typical EEG readings in cases where there is no epilepsy. The accuracy rate the authors of this paper state for classifying these EEG signals is 100% using least square support vector machines. Here are the highlights of the paper:

- The first part of this paper is highlighting a method called ‘optimum allocation’ scheme. This method is used to highlight most favorable representatives with small variability on EEG data.
- This OA based data is then passed onto a principal component analysis algorithm which highlights features that can be best used for a machine learning model.
- While different classifiers are tested for this experiment, the square support vector machines algorithm performs best on the data set with a 100% accuracy rate.

[9] R. Kottaimalai, M. P. Rajasekaran, V. Selvam and B. Kannapiran, "EEG signal classification using Principal Component Analysis with Neural Network in Brain Computer Interface applications," 2013 IEEE International Conference ON Emerging Trends in Computing,

Communication and Nanotechnology (ICECCN), 2013, pp. 227-231, doi: 10.1109/ICE-CCN.2013.6528498.

This paper, unlike other papers that I have looked at, examines different subjects thinking about different cognitive tasks. These cognitive tasks are then predicted via a neural network to yield a continuous output (examining mean square error as the loss function). Here are the highlights of the paper:

- There are five types of cognitive tasks assigned to the subjects that are used in the dataset: baseline tasks, letter task, mathematical task, visual counting task, and geometric figure rotation task.
- A neural network is then applied to these readings to yield a slightly high mean squared error value.
- PCA is also applied to the raw EEG signal value. Following PCA, a neural network is then applied to yield a smaller error and a faster latency for the program overall in predicting the mental task that the subject is thinking of.

[10] Obermaier B, Guger C, Neuper C, Pfurtscheller G (2001) Hidden Markov models for online classification of single trial EEG data. Pattern Recognition Letters 22: 1299–1309

This paper compares EoG (implanted in scalp, more accurate) and EEG (gathered from scalp, more volatile and less accurate) data. It specifically argues that EEG data can be decoded and applied to classify finger movements to attain an accuracy of 77.11%. Here are the highlights of the paper:

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- A five-fold cross validation was applied to the data using an SVM machine learning model.

[11] Huaiyu Xu, Jian Lou, Ruidan Su and Erpeng Zhang, "Feature extraction and classification of EEG for imaging left-right hands movement," 2009 2nd IEEE International Conference on Computer Science and Information Technology, 2009, pp. 56-59, doi: 10.1109/ICCSIT.2009.5234611.

This paper uses a 2003 competition dataset to classify hand movements as either being left or right handed. The paradigm layed out in this paper offers an accuracy rate of up to 82% on the dataset. Here are the highlights of the paper:

- A band pass filter is first applied to the EEG data between 0.3-40Hz since many readings outside of these frequencies are attributed to muscle movement or other noise.

- This paper specifically focused on three channels: C3, C4, and Cz. This was done in an effort to limit the signal-to-noise ratio and focus on only the important aspects of the EEG readings.
- The authors then applied a wavelet transform to the data to reduce the number of data points. They focused on only three particular sub-bands of data: cD6\cD7\cD8.
- Power spectral density is also applied to the dataset using Pwelch from Matlab. This generates a set of features that are around the Mu brain band (this is the band responsible for voluntary movement).
- The features from the PSD method are then added to the wavelet transform coefficients to arrive at the features for the algorithm.
- Linear discriminant analysis is then applied to these features to split up left and right hand movement.

[12] Sarraf, S. (2017, June). EEG-Based Movement Imagery Classification Using Machine Learning Techniques and Welch's Power Spectral Density Estimation. Retrieved April 26, 2021, from https://www.researchgate.net/profile/Saman-Sarraf-3/publication/318281826_EEG-Based_Movement_Imagery_Classification_Using_Machine_Learning_Techniques_and_Welch%27s_Power_Spectral_Density_Estimation/links/59601486458515a357c62f7f/EEG-Based-Movement-Imagery-Classification-Using-Machine-Learning-Techniques-and-Welchs-Power-Spectral-Density-Estimation.pdf

This paper references other literature to determine what signal processing steps were taken to classify various Brain Computer Interface problems. This paper highlighted the following main methods that are related to my project:

- Welch Power Spectral Density to analyze the various activities of the different frequencies.
- K-nearest neighbor to lump groups of power densities together to provide an overall enhanced meaning.
- A support vector machine is then applied to the data in order to further split the data up between 2 particular groups.
- An artificial neural network is then applied to the remaining data to glean additional information to help for specific Brain Computer interface applications (not related to my team’s research).

[13] G. E. Fabiani, D. J. McFarland, J. R. Wolpaw and G. Pfurtscheller, "Conversion of EEG activity into cursor movement by a braincomputer interface (BCI)," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 12, no. 3, pp. 331-338, Sept. 2004, doi: 10.1109/TNSRE.2004.834627.

This paper summarizes the technique of utilizing CAR as a smoothing method. It simply reinforces the standard idea of utilizing CAR and the effectiveness that it brings to preprocessing.

[14] B. O. Peters, G. Pfurtscheller and H. Flyvbjerg, "Automatic differentiation of multichannel EEG signals," in IEEE Transactions on Biomedical Engineering, vol. 48, no. 1, pp. 111-116, Jan. 2001, doi: 10.1109/10.900270.

This paper describes different avenues that CAR can be used within, but the effectiveness within EEG data smoothing is very effective which overall solidifies my idea of utilizing CAR as a pre-processing method.

[15] Robinson N, Guan C, Vinod AP, Ang KK, Tee KP. Multi-class EEG classification of voluntary hand movement directions. J Neural Eng. 2013 Oct;10(5):056018. doi: 10.1088/1741-2560/10/5/056018. Epub 2013 Sep 10. PMID: 24018330

This paper is the main paper that we will be utilizing for implementation. It specifies how cross-validation is needed for regularizing LDA data because LDA can cause overfitting and they depict many different avenues of how that is the case.

[16] Neto E, Biessmann F, Aurlien H, Nordby H and Eichele T (2016) Regularized Linear Discriminant Analysis of EEG Features in Dementia Patients. Front. Aging Neurosci. 8:273. doi: 10.3389/fnagi.2016.00273

This EEG article summarizes the main characteristics of what an EEG signal is, allowing me to understand more ideas of what feature implementation algorithms are viable. For example, any NLP algorithms would not be viable because they don't produce any text, but rather they produce voltage readings instead.

[17] "EEG (Electroencephalogram)." Mayo Clinic, Mayo Foundation for Medical Education and Research, 15 Apr. 2020, www.mayoclinic.org/testsprocedures/eeg/about/pac-20393875.

The regularized linear discriminant analysis can be in many shapes and data sizes, which means that we need to specify which specific regularization we want to use. What I have noticed is that people like to utilize crossvalidation the most, and it seems to be the most effective way of preventing overfitting.

[18] Yaqian Guo, Trevor Hastie, Robert Tibshirani, Regularized linear discriminant analysis and its application in microarrays, Biostatistics, Volume 8, Issue 1, January 2007, Pages 86– 100, https://doi.org/10.1093/biostatistics/kxj035

The article that I referenced above for feature generating utilizes CAR as their smoothing method. This allows for data to be generated in a fashion that is recognizable for feature generating methods.