Analysis of Processing Methods
Comparative Paper

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Researched Methods:

K. Liao, R. Xiao, J. Gonzalez, L. Ding Method (ICA and PSD Method)

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. Shown in **figure 1.1** is the waves in which the algorithm distributes its values from. A five-fold cross validation was applied to the data using an SVM machine learning model. For this research paper, the authors employed PSD and PCA onto EEG data before feeding the newly generated features into an SVM [1]. With the high accuracy attained in this paper of **77.11%,** utilizing an SVM for classification is a good benchmark.

$$P_n(f,\tau_q) = \frac{1}{T}\left|\sum_{t=-\frac{T}{2}}^{\frac{T}{2}-1} X_n(\tau_q + t)\cdot H(t)\cdot \exp\left(i\frac{2\pi}{T}(f-1)t\right)\right|^2$$

$$f = 1,2,\cdots,N_f \quad \tau_q = 1,2,\cdots,N_q$$

Figure 1.1: Depicts the PSD wave distribution equation.

E. Neto, F. Biessmann, H. Aurlien, H. Nordby, T. Eichele (CAR and LDA Method)

LDA assigns observations to corresponding classes based on a set of measurements or predictors by finding an optimal linear transformation that maximizes class separability. It achieves optimal solutions by using predictor vectors (multivariate) that are normally distributed within each class and different groups that have similar covariance. Models can be overfitted and predictability overestimated which is why they aren't going to be 90 and above type accuracy. Noise can be captured from adjacent channels if they are close enough. The solution to these issues could be applying spatial filters and regularization. Regularization with cross validation replaces covariance by a weighted average of the whole sample. This will increase larger eigenvalues while decreasing smaller ones which creates a pooled-covariance matrix. Shown in **figure 1.2**, they achieved an accuracy of **83.0%** with this method.

	Complete set of features		Reduced set of features	
Classifier performances	**cv-ACC**	**AUC**	**cv-ACC**	**AUC**
Model 1 (HC vs. AD)	0.62	0.66	0.67	0.74
Model 2 (HC vs. VaD)	0.65	0.68	0.72	0.77
Model 3 (AD vs. VaD)	0.59	0.62	0.57	0.61
Model 4 (HC vs. AD&VaD)	0.70	0.75	0.77	0.83

Average of the CV accuracy (cv-ACC) and AUC performed for each final classifier using two different sets of features. The Complete Set of Features included a total of 132 predictors and the Reduced Set of Features included variable number of predictors based on automatic feature reduction. Values from [0.5–0.6] = Fail; [0.6–0.7] = Poor; [0.7–0.8] = Fair; [0.8–0.9] = Good; [0.9–1.0] = Excellent.

Figure 1.2: Depicts the RLDA accuracy.

H. Lu, H. Eng, C. Guan, K. Plataniotis, A. Venestansopoulos (CSP Method)

This paper proposed and tested a combination of parameter regularization and aggregation that served to eliminate the issue of having a small sample size of data. Their algorithm, shown in **figure 1.3**, integrates a variety of regularization parameters and the use of the nearest neighbor classifier into the classic CSP algorithm to increase the performance. Using the Regularized Common Spatial Pattern with Aggregation (R-CSP-A) algorithm proposed in the article by Lu et al will benefit our final product by allowing for less error in feature classification, requiring less initial training time and data, and being unique to each user's EEG signal patterns [3]. Once fully implemented the performance of this algorithm will be compared using a static, verified data set and the new data collected using our system to analyze the benefit it brings to our application of low-cost equipment. It is clear that this algorithm is high performing in this setting and will lead to better performance in a majority of the trial cases. According to their paper, they have generated for R-CSP-A **83.4%** accuracy [3].

Input: A set of M EEG trials $\mathbf{E}_{(c,m)_{(s)}}$ for each class of S subjects, where $c = \{1, 2\}$, $m = 1, 2, ..., M$, and $s = 1, ..., S$. A test trial $\mathbf{E}$ for subject s^*, A pairs of β and γ, the number of most discriminative columns from the full projection matrix $Q = 2\alpha$. Subject s^* is considered as the subject of interest and other subjects with $s \neq s^*$ are considered as the generic data.

Output: The class label for $\mathbf{E}$.

R-CSP-A algorithm:

Step 1. Feature extraction

- Obtain $\mathbf{S}_{(c,m)}$ for all subjects $s = 1, ..., S$ according to (1).
- Form $\mathbf{S}_c$ for subject s^* according to (5) and form $\hat{\mathbf{S}}_c$ from other subjects $s \neq s^*$ according to (6).
- For $a = 1 : A$
  - Follow (4), (3), (7), and (8) to get the full projection matrix.
  - Retain the first and last α columns of the full projection matrix to get $\hat{\mathbf{W}}_{(a)}$.
  - Follow (9) and (10) to obtain the feature vector $\hat{\mathbf{y}}_{(a)}$.

Step 2. Aggregation at the matching score level for classification

- For $a = 1 : A$
  - Apply (11) and (12) on $\hat{\mathbf{y}}_{(a)}$ to get $\mathbf{z}_{(a)}$.
  - For $c = 1 : 2$
    - Obtain the nearest-neighbor distance $d(\mathbf{E}, c, a)$.
  - Normalize $d(\mathbf{E}, c, a)$ to $[0, 1]$ to get $\tilde{d}(\mathbf{E}, c, a)$.
- Obtain the aggregated distance $d(\mathbf{E}, c)$.
- **Output** $c^* = \arg\min_c d(\mathbf{E}, c)$ as the class label for the test sample $\mathbf{E}$.

Figure 1.3: Depicts the Lu Algorithm

Overview of Results:

Method	Accuracy
ICA and PSD	77.11%
CAR and LDA	83.0%
CSP	83.4%

References:

[1]. 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].

[2]. Neto E, Biessmann F, Aurlien H, Nordby H, Eichele T. Regularized Linear Discriminant Analysis of EEG Features in Dementia Patients. Front Aging Neurosci. 2016;8:273. Published 2016 Nov 30. doi:10.3389/fnagi.2016.00273

[3]. 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.
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