**Comparative Analysis**

This report aims at building an initial survey for the upcoming BCI project. This includes comparing various Feature Extraction, Feature Selection and Classification techniques used by other authors in their papers between 2011 and 2017.

This is report is divided into 3 sections. The first section tabulates various feature extraction techniques followed by the recorded accuracy of the proposed methods. The second section and third sections compare various Feature Selection and Classification techniques respectively.

**Feature Extraction**

Feature Extraction is one of the most crucial methods in Brain Computer Interfaces. It involves incorporating various signal processing methodologies to extract useful information from raw EEG data.The below table lists some of the most useful feature extraction strategies that can be implemented before advancing.

|  |  |  |  |
| --- | --- | --- | --- |
| Paper Name | Authors | Algorithm Used | Accuracy |
| A Wearable EEG Based Drowsiness Detection System with Blink Duration and Alpha Waves Analysis | V. Kartsch , S. Benatti, D. Rossi, L.Benini | Power Spectral Density/  Fast Fourier Transform | 85% |
| A Motor Imagery using Wavelet Analysis and Spatial Pattern features extraction | Obed Carrera-León, Juan Manuel Ramirez, Vicente Alarcon-Aquino et al. | Common Spatial Patterns from Hilbert transform/Discrete Wavelet Transform | 87.86% |
| A P300-based BCI Classification Algorithm using Median Filtering and Bayesian Feature Extraction | Xiao-ou Li , Feng Wang , Xun Chen, Rabab K. Ward | Median filtering | 90% |
| A Novel Effective Feature Selection Algorithm based on S-PCA and Wavelet Transform Features in EEG Signal Classification | Saadat Nasehi, Hossein Pourghassem | Discrete Wave transform | 91% |

|  |  |  |  |
| --- | --- | --- | --- |
| Paper Name | Authors | Algorithm Used | Accuracy |
| Feature Extraction Technique of EEG based on EMD-BP for motor imagery classification | Dalila Trad, Tarik Al-ani, Mohamed Jemni | Empirical Mode Decomposition followed by band power detection | 0.54(kappa  Coefficient) |
| Time-Frequency Analysis of EEG Asymmetry Using Bivariate Empirical Mode Decomposition | Cheolsoo Park, David Looney, Preben Kidmose, Michael Ungstrup, Danilo P. Mandic | Bivariate Empirical Mode Decomposition | 70% and more |
| Experiments on Using Combined Short Window Bivariate Autoregression for EEG Classification | Tuan Hoang, Dat Tran, Phuoc Nguyen, Xu Huang and Dhamendra Sharma | Auto regression | 70-80% |
| EEG Filtering based on BSS Algorithm and Its Modification for BCI | Manoj Kumar Mukul, Fumitoshi Matsuno | Blind source separation by ICA | ~100% |
| Developing a Logistic Regression Model with Cross Correlation for Motor Imagery Signal Recognition | Siuly and Yan Li, Jinglong Wu and Jingjing Yang | Cross correlation between signals | 90.29% |
| P300 Event Detection using Feature Extraction Technique in FPGA | Kalyana Sundaram et al. | FIR/Hanning filter, Self-organised Fuzzy Neural Network | 90% |

**Feature Selection**

Feature selection is the next method in Brain Computer Interfaces after Feature extraction. It involves selecting a subset of relevant features from various extracted features for use in model construction. It makes training a classifier more efficient by decreasing the size of the effective vocabulary and often increases classification accuracy by eliminating noise features. It’s however different from dimensionality reduction which includes compressing existing data without losing features. Feature Selection doesn’t guarantee increase in accuracy as decrease in available features may lead to decrease in classifier accuracy, it however guarantees decrease in computation cost. The below table lists some of the most useful feature selection strategies that were implemented in some of the published papers.

|  |  |  |  |
| --- | --- | --- | --- |
| Paper name | Authors | Algorithm used | Accuracy |
| GA-SVM based Feature Selection and Parameters Optimization for BCI Research | Lei Wang, Guizhi Xu, Jiang Wang  et al. | Genetic algorithm combined with Support Vector Machines | 89.92% |
| Implementation of automatic feature  selection methods for BCI realization | Andrzej Majkowski, Marcin Kolodziej, Remigiusz J. Rak | t-statistics | ~92% |
| Motion Sickness Estimation System | Chin-Teng Lin, Hua-Chin Lee et al. | Inheritable bi-objective combinatorial genetic algorithm | 73.3% |
| Feature Selection for Brain-Computer Interface Using Nearest Neighbor Information | Yung-Kyun Noh, Byoung-Kyong Min | Jensen-Shannon Divergence using NN method | ~90% |
| Spatial Filter and Feature Selection Optimization based on EA for multi-channel EEG | Yubo Wang, Krithikaa Mohanarangam et al. | Covariance Matrix Adaptation Evolution Strategy | ~75% |

**Classification**

Classification is one of the last but most crucial method in Brain Computer Interfaces. It involves the problem of identifying to which set of [categories](https://en.wikipedia.org/wiki/Categorical_data) a new [observation](https://en.wikipedia.org/wiki/Observation) belongs, on the basis of a [training set](https://en.wikipedia.org/wiki/Training_set) of data containing predefined categoric observations. Classification allows a device to classify the cognitive brain activity based on some selected features into an appropriate category. The table below lists classification methods used by various authors in their papers in context of brain computer interface that were listed as part of feature extraction and feature selection previously.

|  |  |  |  |
| --- | --- | --- | --- |
| Paper Name | Authors | Model Used | Accuracy |
| A Motor Imagery using Wavelet Analysis and Spatial Pattern features extraction | Obed Carrera-León, Juan Manuel Ramirez, Vicente Alarcon-Aquino et al. | Linear Discriminant Analysis | 87.86% |
| A P300-based BCI Classification Algorithm using Median Filtering and Bayesian Feature Extraction | Xiao-ou Li , Feng Wang , Xun Chen, Rabab K. Ward | Bayesian Linear Discriminant Analysis | 90% |
| A Novel Effective Feature Selection Algorithm based on S-PCA and Wavelet Transform Features in EEG Signal Classification | Saadat Nasehi, Hossein Pourghassem | K- Nearest Neighbours | 91% |
| Feature Extraction Technique of EEG based on EMD-BP for motor imagery classification | Dalila Trad, Tarik Al-ani, Mohamed Jemni | Hidden Markov Model | 0.54  (Kappa Coefficient) |
| Time-Frequency Analysis of EEG Asymmetry Using Bivariate Empirical Mode Decomposition | Cheolsoo Park, David Looney, Preben Kidmose, Michael Ungstrup, Danilo P. Mandic |  | >70% |

|  |  |  |  |
| --- | --- | --- | --- |
| Paper Name | Authors | Model Used | Accuracy |
| Experiments on Using Combined Short Window Bivariate Autoregression for EEG Classification | Tuan Hoang, Dat Tran, Phuoc Nguyen, Xu Huang and Dhamendra Sharma | Support Vector Machine with linear kernel | 70-80% |
| EEG Filtering based on BSS Algorithm and Its Modification for BCI | Manoj Kumar Mukul, Fumitoshi Matsuno | Linear Discriminant Analysis | ~100% |
| Developing a Logistic Regression Model with Cross Correlation for Motor Imagery Signal Recognition | Siuly and Yan Li, Jinglong Wu and Jingjing Yang | Logistic Regression | 90.29% |
| P300 Event Detection using Feature Extraction Technique in FPGA | Kalyana Sundaram et al. | Fisher’s Linear Discriminator | 90% |
| GA-SVM based Feature Selection and Parameters Optimization for BCI Research | Lei Wang, Guizhi Xu, Jiang Wang  et al. | Support Vector Machines | 89.92% |
| Implementation of automatic feature  selection methods for BCI realization | Andrzej Majkowski, Marcin Kolodziej, Remigiusz J. Rak | Linear Discriminant Analysis | ~92% |
| Motion Sickness Estimation System | Chin-Teng Lin, Hua-Chin Lee et al. | Support Vector Machines | 73.3% |
| Spatial Filter and Feature Selection Optimization based on EA for multi-channel EEG | Yubo Wang, Krithikaa Mohanarangam et al. | Linear Discriminant Analysis | ~75% |