Feature engineering benchmark for motor related decoding through ECoG signals

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***Abstract*—Invasive Brain Computer Interface (BCI) systems through Electrocorticographic (ECoG) signals require efficient recognition of spatio-temporal patterns from a multi-electrodes sensor array. Such signals are excellent candidates for automated pattern recognition through machine learning algorithms. However, the available data is limited due to the operative procedure required for such dataset creation. The importance of different temporal signatures and individual electrodes can be analyzed through feature extraction techniques. But, the variability of the signal due to non-stationarity is ignored while extracting features and which features to use can be challenging to figure out by visual inspection. In this study, we introduce the signal split parameter to account for the variability of the signal, and we use genetic selection, which allows the selection of the optimal combination of features from a pool of 8 different feature sets.**

***Index Terms*—feature extraction, feature selection, genetic search, ECoG, BCI, machine learning**

I. Introduction

Electrocorticographic (ECoG) signals are obtained via passing a low pass filter on the brain signals [1]. These brain signals are measured via electrodes placed on the brain's cortex region. ECoG signals are extensively used in order to find the focus of seizures in epilepsy (drug resistance) [2]. Brain-machine interfaces use neurophysiological signals, in our case ECoG signals, to predict the action the user wants to perform [3]. ECoG signals have been growing its importance in the studies related to the brain-machine interface [4]. Hence, it is important to efficiently classify ECoG signals coming from the brain of the user.

However, for accurate classification, the appropriate feature extraction technique needs to be identified to capture the difference between the patterns from different classes of data. To create a feature vector to represent the data or feed to the machine learning classifier, features can be exctracted from multiple feature sets and combined, for example features based on Power Spectral Density features consist of one set of features.

Even though there is a significant amount of literature on EcoG data where different feature sets are discussed, the non-stationary nature of singals is often overlooked. Non-stationary signals are those whose statistical properties such as mean and variance change with time. If a signal is of length X then it might have completely different statistical properties from length 0 to X/2 and length X/2 to X, so using a single value (feature) to represent this signal means a lot of information about the signal might be lost.

It is also difficult to manually identify the best feature set for a particular task by visual inspection or other methods. The best features would also depend upon the positioning of the electrodes. Using many different feature sets helps capturing a wide spectrum of time-frequency relationships, but keeping a high dimensional feature set increases computational demand and may add unnecessary noise for the classifier. Hence, a mechanism by which the best combination of features for a particular task can be selected from a large pool of features is required.

The key contributions of this paper are:

1) The analysis and benchmark of 8 different feature sets on Motor Imagery and Motor execution ECoG data.
2) The introduction of a signal split parameter that considers the signal's non stationary nature to increase the performance while using these individual feature sets.
3) We suggest Genetic selection as a method to select the optimal combination of complementary features from the pool of 8 feature sets.
4) We define the accuracy vs Latency trade-off for Motor Imagery and Motor execution BCI systems.

The eight feature sets used in the paper are Modified Stockwell Transform (MST), Relative Wavelet Energy (RWE), Autoregressive Coefficients (AR), Petrosian Fractal Dimension (PFD), Maximum Power Spectral Density (PSD), Frequency at max Power (FMP), Hjorth Complexity (HC), and Mean frequency (MFR). Out of these 8, 5 feature sets have been previously used for motor-related task EcoG data: MST [5], RWE [6], AR [7], PFD [8], HC [9]. But, all of these studies have neglected the effect of the non-stationarity in the signals. The signal split parameter tackles this issue by splitting the signal into different sub segments and extracting features from each sub segment.

To reduce the dimension of the Feature vector, channel selection has been done using different methods such as wrapper method [5], and cross-validation method [8]. Feature selection using the genetic algorithm in EcoG motor imagery has been done by Wei et al. [10] and Aswinseshadri et al. [11]. But, these studies create the final feature vector from only one type of feature set, hence there are no different time-frequency relationships, and it does not allow the genetic algorithm the

Reference	Features Used	Accuracy	Channel Selection Method
Xu et al., 2020 [5]	MST	98	Wrapper Optimization
Xu et al., 2016 [8]	Fractal, Local Binary Pattern	95	Cross Validation
Zhao et al., 2010 [6]	RWE	91.8	PCA
Wei et al., 2008 [12]	CSP	90	Genetic Algorithm
Yan and Guan, 2013 [13]	Wavelet Variance	88	Wavelet Variance
Hammond et al., 2007 [7]	AR, Haar Wavelet Decomposition, Spectral Power Estimates	87	Visual Inspection

TABLE I: State of the Art for the BCI3 dataset

chance to select complementary features. This reduces the chance for the same feature pool to be generalized to other motor-related tasks.

The information about the Pipeline is demonstrated in Fig.1. We extracted various features from these datasets. For feature selection, we do a genetic search-based feature selection. The Genetic algorithm helps reduce the redundant data and only keeps the features determined to be most important. The maximum features the genetic algorithm could choose were restricted, and performance for 8 maximum features to 128 maximum features is presented. Different features can represent wide-ranging spatio-temporal patterns. The goal of feature selection is to find a pool of complimentary features accounting for most patterns. We also quantify the contribution of the features from each feature set in the genetic search.

We evaluate the accuracy achieved by using features from individual feature sets and also from all the feature sets combined. After feature selection using the genetic selection approach we obtained 92% accuracy on the BCI3 dataset 1. The state of the art has been shown in Table I. For the motor basic datasets, we used five-fold cross-validation accuracies and we are unaware of any previous studies which use the motor basic dataset.

Latency is a critical specification of BCI systems. User intention to command latency should be minimum to facilitate a user-friendly and safe system. But information transfer rate is limited by the resolution of the recording system and pattern recognition algorithm. Therefore cues are presented for a long duration (e.g. 3 s in BCI3, Motor Basic) while the actual intention of that movement would be much lesser. Therefore we evaluate system performance for different lengths of time windows to be treated as individual data points in machine learning.

II. Methods

A. Datasets

The information about the datasets is given in Fig.2. The two datasets used to do the feature extraction experiments were BCI3 (i) Dataset and Motor Basic Dataset. In the BCI3 (i) Dataset, there was only 1 participant who had to imagine the action, while in the case of the Motor Basic Dataset, there were 19 subjects who had to act according to the instructions given to them. Out of those 19 subjects, we used 5 subjects in our analysis. All of these 5 subjects had a different number of electrodes and different positioning of these electrodes. In the BCI3 dataset, there was a split of test and training sets. Mot Basic Dataset had no test set and training set separation. These two datasets were publicly available, BCI(i) dataset is available from BCI competition III [14], and Mot Basic is available from Stanford ECoG library [15]

B. Pre-processing

The sampling rate for both datasets was 1000Hz. The signal was downsampled to 100Hz from 1000Hz using the Fourier method. The average of each channel was taken and the resulting signal was subtracted from each channel. The resulting data was then normalized by converting the data points on each channel into Z scores, which is subtracting by the mean and dividing by the standard deviation [16].

C. Feature Extraction

Features can be used to be represent a signal. As shown in Fig. 3, each feature set captures different signatures from the signal, it isn't easy to pinpoint which signature would be appropriate for our task. If only a single feature set is used then only one type of time-frequency relationship can be captured from the signal and also the features from that feature set might not be suitable for identifying the correct signatures from each electrode due to the variation of spatial properties in their signal. For example, the features from the feature set Hjorth complexity might be good for electrode 1 but does not capture the pattern in electrode 24, whereas the features from the feature set Mean frequency does. Hence, we extracted a large pool of features from various different feature sets. The features were extracted from the signal of each electrode. Some of the feature sets: Petrosian Fractal Dimension (PFD) [17], Maximum Power Spectral Density (PSD) [18], Hjorth Complexity (HC) [19] have been previously used in EEG Classification, for PFD we used PyEEG [20] and for HC we used EEGExtract [21] to extract the features.

The features were chosen to capture various different time-frequency relationships from the signal as shown in Fig. 3, where these features are represented on a sine wave composed of various frequencies with a length of 300 time points. According to the fourier decomposition of signals, each signal can be represented as a linear sum of sine and cosine waves functions of different frequency, thus we chose a sine wave to represent the features. The feature was calculated at every such 300 time points. Some features also vary with amplitude; these are represented in Fig. 4. The optimum signal split for each feature was also analysed.

1) Modified S Transform (MST) - Stockwell-Transform (S-Transform) accurately captures the time-frequency information which is contained perceptual motion rhythms. The modified Stockwell-Transform feature was previously used for ECoG-based MI decoding using the BCI3

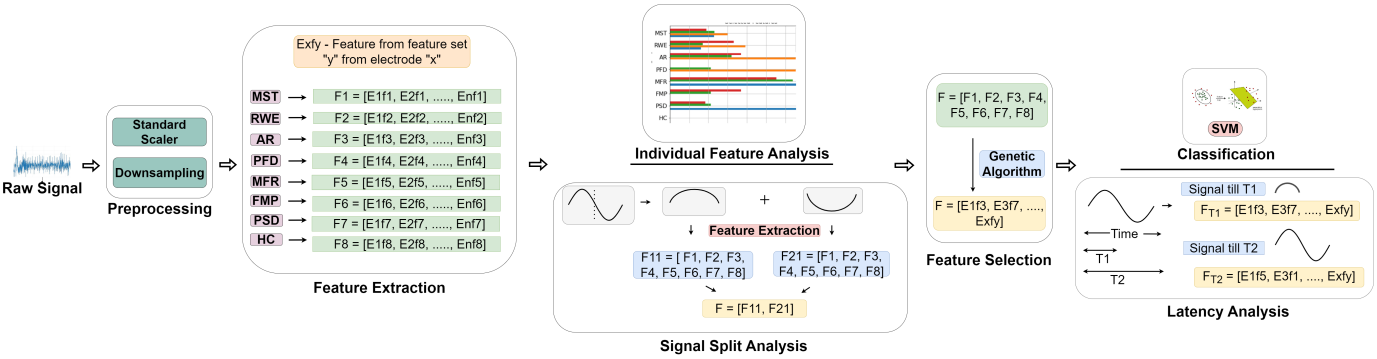

Fig. 1: The pipeline and main idea of the paper have been demonstrated in the figure. A standard scaler normalized the signal from the electrodes, then multiple features were extracted and individual analysis including the signal split was done then these features were concatenated and were passed through a genetic algorithm for feature selection. After feature selection classification was done using either the whole length or reduced length of the signal

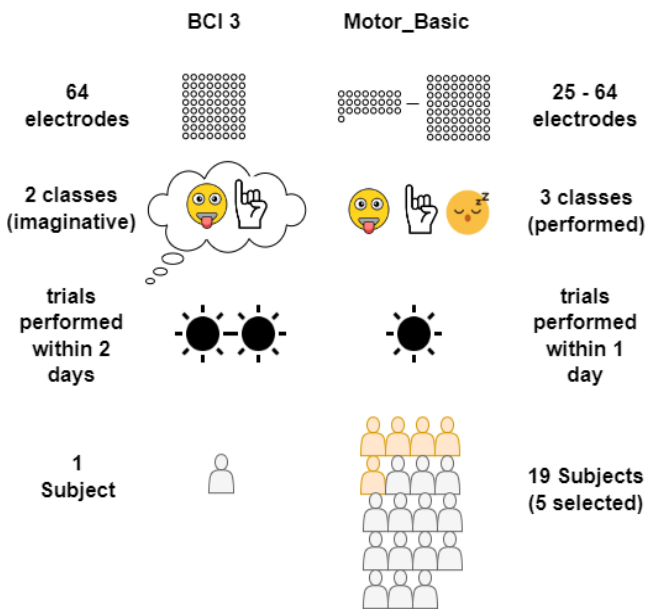

Fig. 2: Information about the datasets. BCI 3 dataset had only 1 subject and contains 64 electrodes whereas the motor basic dataset had 19 subjects out of which 5 were chosen, they contain anywhere between 25 and 64 electrodes.

dataset [5], [22], [23]. [24]. The difference between standard S-Transform and MST is that MST has parameters to vary the height and width of the gaussian window [25]. In the MST feature set multiple features are extracted for a signal hence, error bars are plotted. The mean value and standard deviation of the extracted features has a positive correlation with frequency and amplitude (Fig. 3, Fig.4).

2) Relative Wavelet Energy (RWE) - Relative wavelet energy captures the relative energy in different frequency bands and was previously used with BCI3 dataset [6]. We performed the 2nd-order debauchies transform at the 4th Approximation coefficient (A4), and all 4 detail coefficients (D1-D4) were used as features. The mean value of the extracted features remains constant with change in frequency, but the variance decreases (Fig.3).
3) Autoregressive coefficients (AR Coefficients) - AR model is a simple temporal model where the present value depends on values at previous points. The regressive parameters of the AR model are AR coefficients [26]. AR modelling is a prominent feature extraction technique in signal processing with various applications such as speech signal processing, heart sound processing, and lung sound processing [27]. Hammon et al. [7] have used this feature along with Haar wavelet decomposition coefficients and spectral power estimates to classify the BCI3 dataset. The mean value and variance of the extracted features slightly decreases with increasing frequency (Fig.3).
4) Petrosian Fractal Dimension (PFD) - Fractal dimensions are used to characterize signals and measure their complexity [28]. The method proposed by Petrosian was

a fast method to calculate the fractal dimension [17]. Fractal Intercepts, the intercept of the fitted straight line for fractal dimension, have been previously used to classify the BCI3 dataset [8]. PFD has also been used to classify epileptic signatures from EEG [29]. PFD features have an inverse correlation with frequency (Fig.3), in the case of changing amplitude, the feature value decreases and then becomes constant (Fig.4).

5) Maximum Power Spectral Density The power spectral density is the Power that is present in the signal in the frequency domain. PSD-based features have recently been used for the classification of EEG data [30], [31]. The PSD Features oscillates between different values with changing frequency (Fig.3). It has a direct correlation with amplitude (Fig.4).
6) Frequency at max Power - The frequency at maximum Power in the frequency domain. The feature value increases with frequency, as shown in Fig. 3.
7) Hjorth Complexity: Complexity is one of the parameters from Hjorth Parameters. The parameter of complexity helps in identifying the frequency change. The similarity between a sine wave and the signal is measured by this parameter. The closer the signal is to the sine wave, the closer the value is to 1 [19]. Hjorth complexity was previously used to classify EcoG data in non-human primates [32]. Hjorth Complexity and other Hjorth parameters are commonly used as a feature extraction technique for the classification of EEG data [33], [34]. [35], [36]. The HC feature value shows a very complex relationship with changing frequency and amplitude (Fig.3, Fig.4).
8) Mean frequency feature vector - The mean frequency of the Fourier transformed data was used. The feature value increases with frequency(Fig. 3) but shows a complex relationship with Amplitude.

D. Feature Selection

Feeding all the features would lead to higher dimensional feature vectors and hence more trainable parameters of the machine learning classifier. Features capturing redundant and irrelevant features makes training robust classifier challenging. Hence, a genetic algorithm feature selection mechanism is used to intelligently select the optimal combination of features.

The genetic algorithm randomly initializes multiple sequences of 0s and 1s equivalent to the length of the feature vector. 1 means the feature is selected and 0 means it is not. This array of 0s and 1s is called chromosomes. Multiple chromosomes consist a population. The fitness of each chromosome is evaluated by the five fold cross validation accuracy on the training data. Mutations and crossovers happen between a population to generate new and fitter chromosomes. After a specified number of generations the fittest chromosome is chosen, and hence a subset of features based on that chromosome is selected.

Feature	No. of Features per Electrode Signal
MST	35
RWE	5
AR	2
PFD	1
FMP	1
MFR	1
FMP	1
PSD	1
HC	1

TABLE II: The number of features per signal for individual feature set.

E. Classification

Machine learning enables learning patterns from the example data directly without relying on predefined equations as a model [37]. The Machine learning classification algorithms we used in this study are sklearn's Random Forest and Support vector machine (SVM) [38]. Random Forest is a supervised machine learning algorithm based on the ensemble learning technique. In ensemble learning, we combine various classifiers [39]. In the random forest algorithm, several decision trees are present on various random subsets of the chosen data, and the average is taken to improve the prediction accuracy of the dataset. The more the number of decision trees, the better accuracy is achieved [40]. SVM creates a hyperplane (or a line in the case of only 2 features) or a decision boundary around the data points to classify a new data point [41].

III. Results and Discussion

A. Individual Feature Analysis

As shown in Table II, there were multiple features extracted from the signal of one electrode in the feature sets of MST, RWE, and AR. For example, there were 5 features per channel (electrode) of the Relative Wavelet Energy feature set, and as there are 64 electrodes, there were 64*5 = 320 features in each trial for the Relative Wavelet Energy feature set.

Xu et al. [5], Zhao et al. [6], and Hammon et al. [7] respectively managed to achieve 98%, 91.8% and 87% using MST, Relative Wavelet Energy, and Auto-regressive coefficients (along with spectral power estimate features). The difference in individual features for BCI3 in our case Fig.II between the accuracies in our case and the above is due to various factors, including differences in preprocessing schemes, Filtering, Dimensionality reduction, Feature parameters, Channel Selection, and Classifiers and Classifier Hyperparameters.

The individual feature accuracies set a baseline to compare with signal split feature analysis. In signal split, the signal is split into several sub segments; for example, a signal split of 2 means the signal of length 3000 is split into 2 sub segments each of length 1500. The features are extracted on each of the sub segments and then concatenated. As demonstrated in Fig. 3, there is significant variation in the feature values as the frequency and amplitude of the sine wave change, the changing amplitude and frequency of the sine wave replicates a real-world signal where amplitude and frequency are continuously

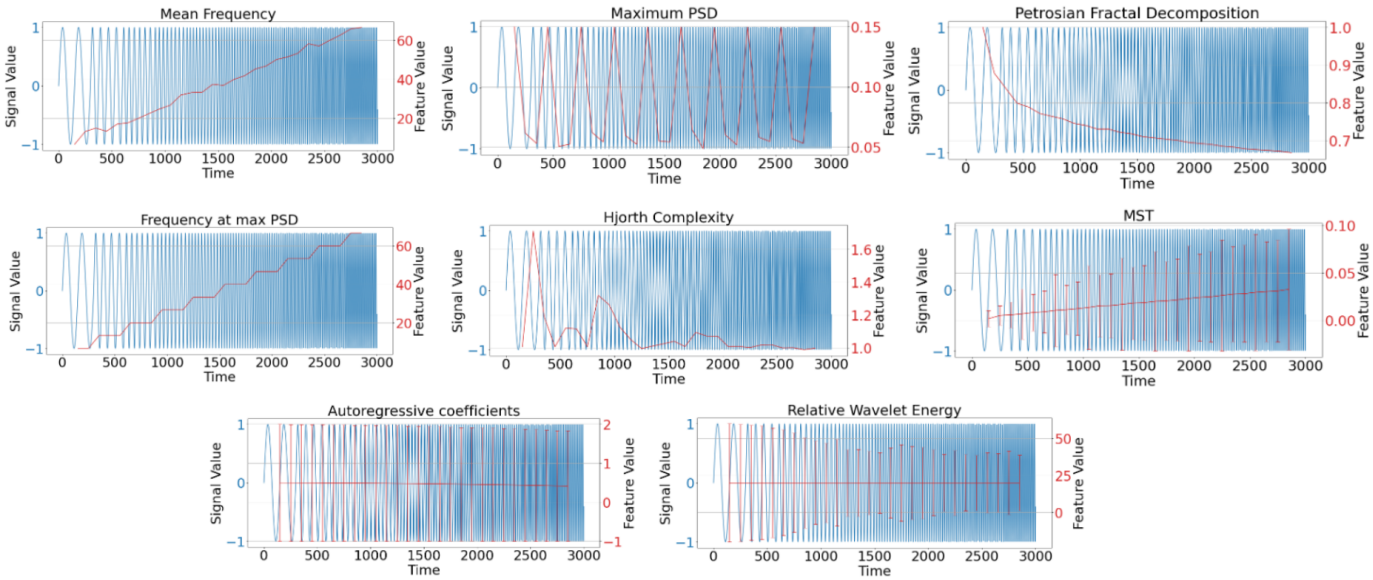

Fig. 3: Feature sets represented on a sine wave of different frequencies: Sine waves of frequencies 20, 40, 60, 80, 100, 120, 140, 160, 180, and 200 were concatenated. Each sine wave was of length 300, and the features were calculated. The red line depicts the feature values, and the blue line wave depicts the concatenated sine wave. The feature sets MST, AR, and RWE extract multiple features per signal; hence error plots are plotted for them.

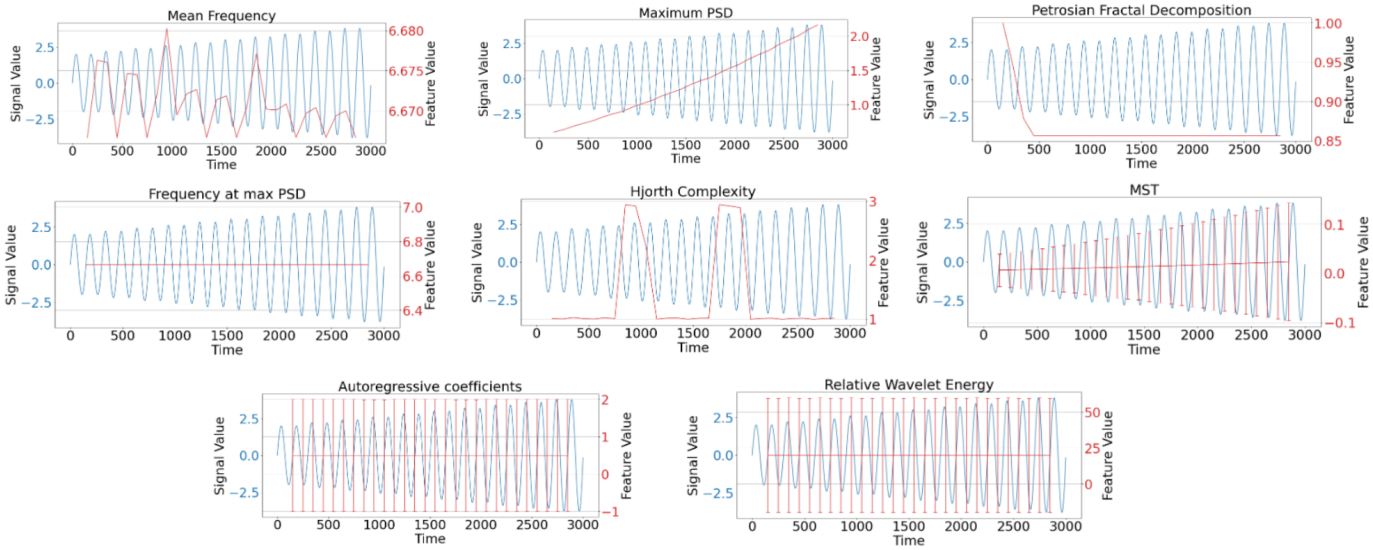

Fig. 4: Some features depend on the amplitude also, these have been represented on a concatenated sine wave of different amplitudes but of the same frequency. Each sine wave was of length 300, and the features were calculated for each sine wave

changing. So if we take a single value for the whole signal, it would not represent it as accurately. Thus, we use the signal split parameter, which divides the signal into n sub signals on which the value of the feature is calculated and thus the non-stationary nature of the signal is accounted for.

In table III we see that across the 8 feature sets and 6 subjects, the accuracy increases in 43 out of 48 cases. It can also be observed that different feature sets have different optimal splits. For feature sets MST, AR, MFR, and FMP the average optimal split is between 2 and 3.5, which means these feature sets give a better result when they are extracted on a long length of the signal, so these can be called long-range features. The feature sets RWE and PFD had an average optimal split of 4.5 and 4.67, these feature sets give better results when used for a moderate length of the signal, thus these are called mid-range features. The feature sets of PSD and HC had an average optimal split of 10.67 and 13.33, these feature sets would be most useful when used for short lengths, so these are short range features. Thus, a signal split parameter should also be optimized whenever individual features are used

Feature Set	Dataset	Maximum accuracy before signal Split (%)	Maximum accuracy after signal split (%)	Optimum Signal split
MST	BCI3	86	86	1
	GC_MOT	65.27	76.03	3
	JC_MOT	70.2	89.3	2
	JT_MOT	43	57.8	3
	WC_MOT	67.7	85.07	2
	RR_MOT	83.47	98.33	10
RWE	BCI3	83	86	2
	GC_MOT	67.73	71.03	6
	JC_MOT	78.4	84.23	3
	JT_MOT	48.03	50.47	10
	WC_MOT	74.33	85.07	3
	RR_MOT	86.83	93.43	3
AR	BCI3	83	86	2
	GC_MOT	67.73	71.03	6
	JC_MOT	78.4	84.23	3
	JT_MOT	48.03	50.47	10
	WC_MOT	74.33	85.07	3
	RR_MOT	86.83	93.43	3
PFD	BCI3	84	89	2
	GC_MOT	56.83	66	2
	JC_MOT	52.07	71.87	6
	JT_MOT	57	58.63	2
	WC_MOT	68.67	84.27	10
	RR_MOT	67.77	79.33	6
MFR	BCI3	82	82	1
	GC_MOT	67.77	68.6	2
	JC_MOT	79.3	84.3	2
	JT_MOT	47.2	54.5	3
	WC_MOT	74.3	82.63	2
	RR_MOT	88.47	95.03	3
FMP	BCI3	74	83	3
	GC_MOT	50.47	59.4	2
	JC_MOT	56.07	66.87	3
	JT_MOT	51.23	51.23	1
	WC_MOT	66.9	66.9	1
	RR_MOT	74.37	92.63	10
PSD	BCI3	69	82	30
	GC_MOT	60.23	72.7	2
	JC_MOT	72.63	80.27	2
	JT_MOT	48	51.23	10
	WC_MOT	74.3	74.33	10
	RR_MOT	82.73	90.17	10
HC	BCI3	54	61	2
	GC_MOT	50.4	51.23	30
	JC_MOT	50.4	52.9	15
	JT_MOT	51.23	51.23	1
	WC_MOT	50.4	52.9	2
	RR_MOT	49.57	57.1	30

TABLE III: Individual Feature analysis: Accuracy for each feature in the BCI3 dataset, before and after the signal split analysis

to achieve the best results.

B. Feature selection

Although in the case of MST feature for BCI3, the accuracy is 86% it consists of 2240 (MST extracts 35 features from each electrode, and there are 64 electrodes hence 35*64=2240 features) features, and according to Table IV the accuracy when all the features are combined is 90% whereas genetic selection achieves 92% using 8 max features. similarly, as in the BCI3 dataset, the accuracy increases significantly in

Subject	Total Features Per Trial	Maximum accuracy before Feature Selection (%)	Maximum accuracy after Feature Selection (%)
BCI3	3136	90	92
GC_MOT	3136	70.2	91.76
JC_MOT	2352	83.36	90.17
WC_MOT	3136	77.6	92.6
JT_MOT	3038	47.87	90.93
RR_MOT	2401	90.1	89.3

TABLE IV: Feature Selection analysis: The accuracy for the subject before and after the feature selection. The total number of features per trial are the feature values that were extracted for all 8 set features and all electrodes and then combined.

5 out of the 6 subjects, and in one subject, the accuracy only slightly decreases by 0.8% as shown in Fig. 5, the maximum accuracy is obtained by the genetic algorithm between 8 and 64 max features which is significantly less than the total number of features. This means that the genetic selection method can obtain an optimal combination of features that complement each other. A similar approach was used by Wei et al. (2010) [42], and Wei et al. (2008) [12] they used the genetic algorithm to select the best combination of channels and then extracted features from the selected channels. Although, the difference from our approach is that we selected the features after extraction of these features from all of the channels, as our objective was to create a pool of selected features that best complement each other.

Fig. 5 shows the number of selected features in each feature set after genetic selection with maximum features as 16, 32, 64, and 128. It shows how the genetic algorithm selects the features in different ratios to give the perfect combination.

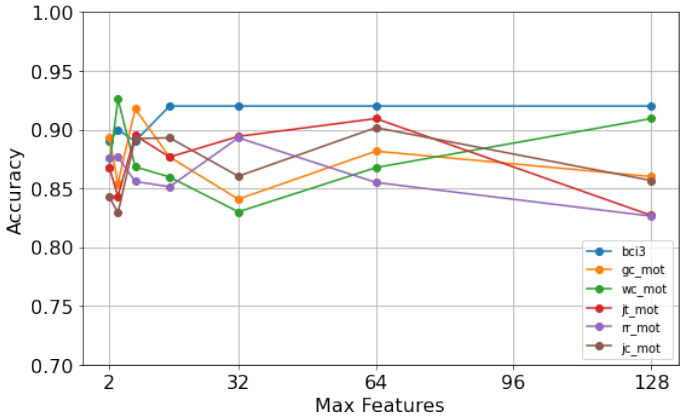

Fig. 5: Accuracy vs Max Features for BCI3 and all motor basic dataset subjects. The max features are the maximum number of features that the genetic algorithm could select.

Fig. 6 shows the number of selected features in each broad feature set after genetic selection with max features as 16, 32, 64, and 128. It shows how the genetic algorithm selects the features in different ratios to give the perfect combination. Any

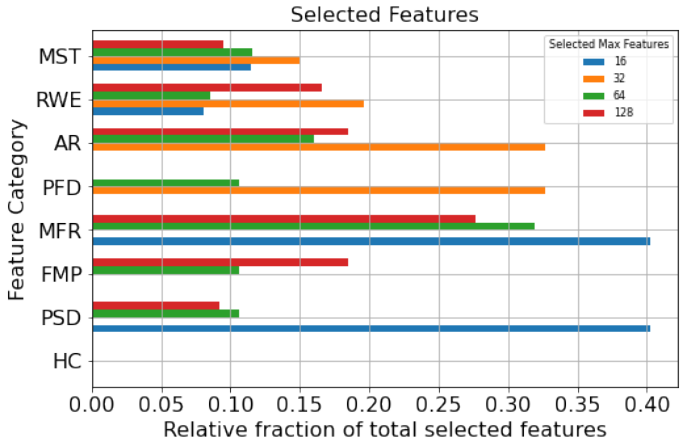

Fig. 6: The number of features selected in the BCI3 dataset from each of the 8 feature sets. The number of features from each feature set is different, so to give the relative fraction of a set, the selected features from a feature set were normalized by dividing by the number of features in that particular set.

feature from the feature set HC is not selected, this means that the genetic algorithm filters out any feature from this feature set as it thinks that it is not in the best 16, 32, 64, or 128 features.

C. Latency Analysis

In the case of motor imagery, the participant was told to imagine the movement when the recording of data started. Hence, it is not clear if the whole 3 seconds of data is required for classification, so we wanted to see if we could achieve good accuracy with the reduced size of the signal. The signal from the first 500, 1000, 1500, or 3000ms was used to compute the features, and the classifier output was used to evaluate the system's latency.

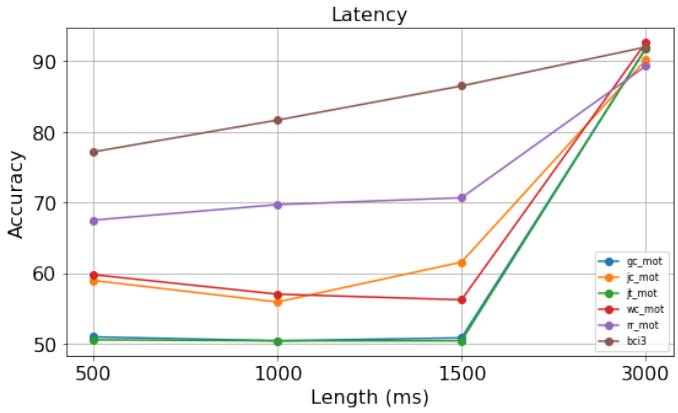

Fig. 7: Accuracy vs Latency for all the datasets. The latency is defined as the time after the trigger of the action is performed. The trials were separated into segments of one-half, one-third, and one-sixth length of the entire sequence

We observed that in the case of the motor imagery (bci3 dataset) if we use the signal with half of the length of the entire sequence, the time window signal we can achieve accuracy comparable to when we consider the full segment (Fig. 7). It is also observed in Fig. 7 that the accuracy of classification decreases with a decrease in the length of the segment. Although, the reduced signal results in a decrease in accuracy it results in quicker decision-making by the BCI.

In the case of the motor execution datasets, the accuracy increases sharply when the whole length of the signal is considered. This means that it is difficult to classify motor execution data with a reduced length of the signal.

IV. Conclusion

Brain computer interfaces require efficient classification techniques. Various approaches for efficient classification exist, including deep learning and machine learning techniques. Machine learning techniques generally focus on a particular feature extraction technique. Our goal in this study was to enhance the accuracy while using a particular feature by introducing a signal split parameter. We also encourage using a large feature pool and genetic selection to find an optimal combination of features. The genetic algorithm is time consuming to train but once the optimal combination is found the classfication becomes faster as the dimensionality of the data is reduced and due to the reduced dimensionality the genetic algorithm is also a hardware friendly technique. We also define the trade-off between latency and accuracy in the Brain-computer interface.

The current state of the art for BCI3 includes deep learning approaches which use LSTM or CNN for classification [43], [44], although more accurate, these methods require high processing power and are generally subject to the BlackBox problem which makes it harder for programmers to understand the functioning of the algorithms and makes it difficult to tweak them. This paper focuses mainly on Machine Learning and Feature extraction methods.

A major limitation of our work is the absence of deep-learning approaches, which is out of this work. Although, the major problem with using Deep Learning approaches with EcoG is the lack of data and the black box problem. Hence, we suggest that end-to-end deep learning methods may not be the best solution, rather, some feature extraction might be optimal.

V. Appendix

References

[1] DL Keene, S Whiting, and ECG Ventureyra. Electrocorticography. *Epileptic Disorders*, 2(1):57–64, 2000.

[2] David Roberts, Michael Higgin, Enrique Ventureyra, et al. Alfentanil mediated activation of epileptiform activity in the electrocorticogram during resection of epileptogenic foci. *Canadian journal of neurological sciences*, 24(1):29–36, 1997.

[3] Richard A Andersen, Sam Musallam, and Bijan Pesaran. Selecting the signals for a brain–machine interface. *Current opinion in neurobiology*, 14(6):720–726, 2004.

[4] Aysegul Gunduz and Gerwin Schalk. Ecog-based bcis. *Brain–Computer Interfaces Handbook*, pages 297–322, 2018.

[5] Fangzhou Xu, Wenfeng Zheng, Dongri Shan, Qi Yuan, and Weidong Zhou. Decoding spectro-temporal representation for motor imagery recognition using ecog-based brain-computer interfaces. *JIN*, 19(2):259–272, 2020.

[6] Hai-bin Zhao, Chun-yang Yu, Chong Liu, and Hong Wang. Ecog-based brain-computer interface using relative wavelet energy and probabilistic neural network. In *2010 3rd International Conference on Biomedical Engineering and Informatics*, volume 2, pages 873–877. IEEE, 2010.

[7] Paul S Hammon and Virginia R de Sa. Preprocessing and meta-classification for brain-computer interfaces. *IEEE Transactions on Biomedical Engineering*, 54(3):518–525, 2007.

[8] Fangzhou Xu, Weidong Zhou, Yilin Zhen, Qi Yuan, and Qi Wu. Using fractal and local binary pattern features for classification of ecog motor imagery tasks obtained from the right brain hemisphere. *International Journal of Neural Systems*, 26(06):1650022, 2016.

[9] Lin Yao and Mahsa Shoaran. Enhanced classification of individual finger movements with ecog. In *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, pages 2063–2066. IEEE, 2019.

[10] Qingguo Wei, Xiaorong Gao, and Shangkai Gao. Feature extraction and subset selection for classifying single-trial ecog during motor imagery. In *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 1589–1592. IEEE, 2006.

[11] K Aswinseshadri and V Thulasi Bai. Feature selection in brain computer interface using genetics method. In *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, pages 270–275. IEEE, 2015.

[12] Qingguo Wei and Wei Tu. Channel selection by genetic algorithms for classifying single-trial ecog during motor imagery. In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 624–627. IEEE, 2008.

[13] Shi Yu Yan and De Jun Guan. Ecog classification research based on wavelet variance and probabilistic neural network. In *Applied Mechanics and Materials*, volume 380, pages 2280–2285. Trans Tech Publ, 2013.

[14] Thomas Lal, Thilo Hinterberger, Guido Widman, Michael Schröder, N Hill, Wolfgang Rosenstiel, Christian Elger, Niels Birbaumer, and Bernhard Schölkopf. Methods towards invasive human brain computer interfaces. *Advances in neural information processing systems*, 17, 2004.

[15] Kai J Miller. A library of human electrocorticographic data and analyses. *Nature human behaviour*, 3(11):1225–1235, 2019.

[16] Steven D Colan. The why and how of z scores. *Journal of the American Society of Echocardiography*, 26(1):38–40, 2013.

[17] Arthur Petrosian. Kolmogorov complexity of finite sequences and recognition of different preictal eeg patterns. In *Proceedings eighth IEEE symposium on computer-based medical systems*, pages 212–217. IEEE, 1995.

[18] Silvia Maria Alessio. Digital signal processing and spectral analysis for scientists: concepts and applications. 2015.

[19] Bo Hjorth. Eeg analysis based on time domain properties. *Electroencephalography and clinical neurophysiology*, 29(3):306–310, 1970.

[20] Sylvain Baillet, Karl Friston, and Robert Oostenveld. Academic software applications for electromagnetic brain mapping using meg and eeg, 2011.

[21] Sari Saba-Sadiya, Eric Chantland, Tuka Alhanai, Taosheng Liu, and Mohammad Mahdi Ghassemi. Unsupervised eeg artifact detection and correction. *Frontiers in Digital Health*, 2:57, 2020.

[22] Wenfeng Zheng, Fangzhou Xu, Minglei Shu, Yingchun Zhang, Qi Yuan, Jian Lian, and Yuanjie Zheng. Classification of motor imagery electrocorticogram signals for brain-computer interface. In *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, pages 530–533. IEEE, 2019.

[23] F Xu, W Zhou, Y Zhen, and Q Yuan. Classification of ecog with modified s-transform for brain-computer interface. *Journal of Computational Information Systems*, 10(18):8029–8041, 2014.

[24] Hongli Chang and Jimin Yang. Genetic-based feature selection for efficient motion imaging of a brain–computer interface framework. *Journal of neural engineering*, 15(5):056020, 2018.

[25] Said Assous and Boualem Boashash. Evaluation of the modified s-transform for time-frequency synchrony analysis and source localisation. *EURASIP Journal on Advances in Signal Processing*, 2012(1):1–18, 2012.

[26] Karl J Friston. Statistical parametric mapping. In *Neuroscience databases*, pages 237–250. Springer, 2003.

[27] Rajkumar Palaniappan, Kenneth Sundaraj, Sebastian Sundaraj, N Huliraj, SS Revadi, and B Archana. Pulmonary acoustic signal classification using autoregressive coefficients and k-nearest neighbor. In *Applied Mechanics and Materials*, volume 591, pages 211–214. Trans Tech Publ, 2014.

[28] BS Raghavendra and D Narayana Dutt. Signal characterization using fractal dimension. *Fractals*, 18(03):287–292, 2010.

[29] Luis Alfredo Moctezuma and Marta Molinas. Classification of low-density eeg for epileptic seizures by energy and fractal features based on emd. *Journal of biomedical research*, 34(3):180, 2020.

[30] Wei Bin Ng, A Saidatul, YF Chong, and Z Ibrahim. Psd-based features extraction for eeg signal during typing task. In *IOP Conference Series: Materials Science and Engineering*, volume 557, page 012032. IOP Publishing, 2019.

[31] Zhi Ying Ong, A Saidatul, and Z Ibrahim. Power spectral density analysis for human eeg-based biometric identification. In *2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)*, pages 1–6. IEEE, 2018.

[32] Lin Yao, Jonathan L Baker, Nicholas D Schiff, Keith P Purpura, and Mahsa Shoaran. Predicting task performance from biomarkers of mental fatigue in global brain activity. *Journal of neural engineering*, 18(3):036001, 2021.

[33] Ömer Türk, Mesut Şeker, Veysi Akpolat, and Mehmet Siraç Özerdem. Classification of mental task eeg records using hjorth parameters. In *2017 25th Signal Processing and Communications Applications Conference (SIU)*, pages 1–4. IEEE, 2017.

[34] Seung-Hyeon Oh, Yu-Ri Lee, and Hyoung-Nam Kim. A novel eeg feature extraction method using hjorth parameter. *International Journal of Electronics and Electrical Engineering*, 2(2):106–110, 2014.

[35] Rami J Oweis and Enas W Abdulhay. Seizure classification in eeg signals utilizing hilbert-huang transform. *Biomedical engineering online*, 10(1):1–15, 2011.

[36] Mesut Şeker and Mehmet Siraç Özerdem. Classification of eeg data sets with hilbert transform. In *2016 24th Signal Processing and Communication Application Conference (SIU)*, pages 1949–1952. IEEE, 2016.

[37] Jaime G Carbonell, Ryszard S Michalski, and Tom M Mitchell. An overview of machine learning. *Machine learning*, pages 3–23, 1983.

[38] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[39] Omer Sagi and Lior Rokach. Ensemble learning: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(4):e1249, 2018.

[40] Nasiba Mahdi Abdulkareem, Adnan Mohsin Abdulazeez, et al. Machine learning classification based on radom forest algorithm: A review. *International Journal of Science and Business*, 5(2):128–142, 2021.

[41] William S Noble. What is a support vector machine? *Nature biotechnology*, 24(12):1565–1567, 2006.

[42] Qingguo Wei, Zongwu Lu, Kui Chen, and Yuhui Ma. Channel selection for optimizing feature extraction in an electrocorticogram-based brain-computer interface. Technical Report 5, 2010.

[43] Mamunur Rashid, Minarul Islam, Norizam Sulaiman, Bifta Sama Bari, Ripon Kumar Saha, and Md Jahid Hasan. Electrocorticography based motor imagery movements classification using long short-term memory (lstm) based on deep learning approach. *SN Applied Sciences*, 2(2):1–7, 2020.

[44] Fangzhou Xu, Fenqi Rong, Yunjing Miao, Yanan Sun, Gege Dong, Han Li, Jincheng Li, Yuandong Wang, and Jiancai Leng. Representation learning for motor imagery recognition with deep neural network. *Electronics (Switzerland)*, 10(2):1–13, jan 2021.