Cluster Separation Index Suggests Usefulness of Non-Motor EEG Channels in Detecting Wrist Movement Direction Intention

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Abstract — **The aim of the study was to select the best electroencephalogram features and channel locations for detection of wrist movement intentions. The detected intentions can be used in brain-computer interfaces (BCIs) either for direct control of an artificial or virtual hand, or they can be used as an underlying binary code for execution of other tasks. 28 channel EEG was recorded while a subject performed wrist movements in four directions. Four basic feature types were extracted in the time and frequency domains for each channel following optimized filtering of the signals. The signals were split into planning and execution segments, respectively. Various delays and anticipation lengths were taken into account for each of the features, thus totaling 93 different features. The potential performance of each feature and channel for use in the classification of the EEG signals was analyzed by estimating the relative class overlap using the Davies-Bouldin Index (DBI), a widely used measure for estimating cluster separation. The best feature/channel configurations contained both channels that were close and channels that were far from motor areas. A statistical test using the channel/feature configurations that yielded the lowest 5% DBI values for motor and for non-motor channels yielded no significant difference (α= 0.05) between these two channel populations.**

The scope and depth of the study was limited. Plus, important parts of the signal had to be discarded to rule out interference stemming from saccadic eye movement. However, our results do suggest more attention should be paid to non-motor areas in earlinked EEG data even when investigating movement related BCIs.

Keywords — **Brain-Computer Interface, Movement Related Potentials, Cluster Separation, EEG**

I. INTRODUCTION

Among the various approaches with potential towards EEG-based brain-computer interfaces (see [1] for a review on the subject), the use of motor related potentials (MRPs) has a number of positive points, at least in principle. MRPs are naturally generated by the user without the need for biofeedback, thus reducing subject training requirements, and they can allow for relatively quick responses in a BCI system. The detected motor intentions can then be used either for direct control of an artificial or virtual hand, or they can be used as an underlying binary code for execution of other tasks.

Much research into the detection of motion related potentials for use in BCIs has been focused of differentiating between movements in different limbs, such as right vs. left hand movement [2]. This has advantages as discriminating activity in the brain is likely to occur in different and far apart locations for each of the movement classes, thus allowing for easier classification. In this study, on the other hand, the possibility of detecting movement intention about a single joint complex (i.e., the right wrist) was investigated with the different classes being the various directions of movement. The present study is an extension of the work shown in [3]. In that study we concluded that non-motor channels may play a role in class separation of MRPs. However, that study used only histogram overlap areas to lead to this conclusion. Thus, in the present study we extend our analysis to include a measure of class separation based on a commonly used cluster separation index, the Davies-Bouldin Index (DBI) [4]. This index provides a measure of class separation. The smaller its value, the smaller the overlapping between the classes. By using this measure, one can then eliminate the features that manifest large class separation and that will thus make the classification task more difficult.

This study focused on right-side wrist movements. 93 different features from, the time and frequency domains were extracted for each of 28 channels. The DBI was then applied to all features to determine which combination of feature and channel yielded the best class separability for four different wrist movement directions.

II. METHODOLOGY

A. Experimental Protocol and Pre-Processing

For this study, data were obtained from a single subject. 28 channels of earlinked referential EEG data were recorded using a NeuroScan^{TM} Symamp system with the electrodes positioned according to the standard 10-20 system. Because the investigated movements were for the right hand, only left hemisphere channels (and those near the areas of interest) were taken into account. Sampling was done at 2 kHz for convenience as 4 EMG channels were simultaneously recorded from selected wrist muscles (with the same equipment) in connection with another study. Table I shows the channel numbers and their respective locations as designated in the 10-20 system. The experimental protocol was approved by an ethics committee (University of Strathclyde) and the subject provided written consent.

TABLE I
EEG CHANNELS AND THEIR LOCATIONS

ch#	Loc.	ch#	Loc.	ch#	Loc.
1	F1	10	FC2	19	C3
2	F5	11	P7	20	FCZ
3	FC1	12	P3	21	FZ
4	PZ	13	CP3	22	P2
5	FC5	14	CPZ	23	C2
6	C5	15	CZ	24	T7
7	CP5	16	CP1	25	FT7
8	P1	17	C1	26	FC3
9	P5	18	TP7	27	F3
				28	CP2

The data consisted of a series of repeated movement trials initiated by audio and visual cues. The subject looked at an X vs. Y plot of wrist positions. An initial visual cue was presented indicating where to move the wrist. An audio cue then instructed the subject to move the wrist to the target as fast as possible and maintain the new position until another audio cue was given to move back. There were 4 different visual stimuli corresponding to the following wrist movement classes:

1. Up (i.e., radial deviation of wrist),
2. down (i.e., ulnar deviation of wrist),
3. left (i.e., flexion of wrist),
4. right (i.e., extension of wrist).

The EEG signals were lowpass filtered at 60Hz to help prevent aliasing, after which the signal was downsampled to the more standard 125Hz. The signal was then bandpass filtered at 5Hz-15Hz, to emphasize the alpha band, 12-32Hz to emphasize the beta band, and 5Hz-32Hz to emphasize the whole range of frequencies where MRPs might be present. Several filters types and configurations were tested. The best filter (elliptic, order 8) was chosen based on two criteria: 1) computational cost if used in a real-time system, and 2) energy based signal-to-noise ratios for the various bands of interest.

B. Feature Extraction

After the signals were filtered, two signal segment types were extracted from each trial for further analysis. The segments were respectively related to the *planning* and the movement *execution* stages of each trial as these were expected to produce different best feature choices. The first segment contained data following the visual clue, but with a 215ms delay to account for possible saccadic reactions, and continued until the first audio stimulus. This consisted of the planning stage data and lasted 750ms. The length of the delay was determined using [5]. By taking such a delay into account, we have possibly eliminated valuable movement planning data, thus leading to worse results than may have been necessary. However, in this way we are more confident that the class separation under investigation is more likely to be related to the wrist movements rather than to an oculomotor response to the visual clue. Our results are thus applicable only to a situation whereby saccadic interference in the signals is removed.

The second segment contained data starting at the first audio stimulus, with a delay of 100ms to account for any non-wrist reaction to the stimulus, and continued until the second audio clue was given. This was the movement execution data and lasted 2000ms. In this paper we report results for overall class separation, i.e., as a result of both planning and execution data pooled together, as well as results for each individual phase.

The following features types were extracted for each segment, channel, and frequency band:

1. The total band power (estimated using Welch's method),
2. the dominant frequency within a band,
3. the time-domain variance, and
4. the mean amplitude (measured using 100ms long jumping windows).

The mean amplitude was calculated using 100ms vectors as this is roughly the window within which the signal may be assumed to be quasi stationary. For each feature above, various anticipation (i.e., planning) and delay (i.e., execution) values were investigated as well. A total of 93 features were thus investigated (Table II). This produced a total of 93*28 = 2604 feature values for each trial. These values were then used in a cluster separation analysis.

C. Feature Selection and Class Separability

In order to decide which of the various features and channels would be of most use in a subsequent classification task, the Davies Bouldin Index [4] was used.

To obtain the DBI, the *i* cluster to *j* cluster similarity (R_{ij}, where each cluster is a movement class) had to be estimated along with the distance between the cluster's centroids (M_{ij}) (note that the discussion here is based on two clusters for simplicity only; our study actually used four clusters).

Cluster similarity is given by

$$\mathrm{R}_{ij} \equiv \frac{S_i + S_J}{M_{ij}} \ ,$$

where the S_i and S_j are the dispersions of the i^{th} and j^{th} clusters, respectively.

The intercluster distance is given by

$$M_{ij} = \left\{ \sum_{K=1}^{N} \left| a_{ki} - a_{kj} \right|^p \right\}^{\frac{1}{p}} \ ,$$

where a_{ki} is the centroid of cluster *i*. p=2 in our study (i.e., *M*, the Minkowski distance, becomes the Euclidean distance between the centroids).

TABLE II

FEATURE NUMBERS AND THEIR DESCRIPTION. FEATURE STARTING WITH A *p* REFER TO THE PLANNING PHASE, WHEREAS THOSE STARTING WITH AN *m* REFER TO MOVEMENT EXECUTION. THE NUMBERS AT THE END OF A FEATURE'S DESCRIPTIVE NAME INDICATE THE TIME LOCATION OF THE FEATURE AFTER AN AUDIO STIMULUS FOR PLANNING AND AFTER VISUAL STIMULUS FOR MOVEMENT EXECUTION SEGMENTS (PLUS THE ABOVE REMOVED SEGMENTS IN BOTH CASES). THE NUMBERS INDICATE THE LOCATION OF THE 100ms WINDOW FROM WHICH THE FEATURE WAS EXTRACTED. E.G., pMeanBetaAmp8 DENOTES THE MEAN AMPLITUDE OF THE RECTIFIED SIGNAL, FILTERED TO EMPHASIZE THE BETA BAND, IN THE WINDOW FROM 800-900ms AFTER THE AUDIO STIMULUS IS GIVEN.

Feat. # and Description		Feat. # and Description		Feat. # and Description		Feat. # and Description		Feat. # and Description	
1	pAlphaPower	21	pMeanAlphaAmp3	41	mMeanAlphaAmp16	61	mMeanBetaAmp11	81	mMeanTotalAmp6
2	mAlphaPower	22	pMeanAlphaAmp4	42	mMeanAlphaAmp17	62	mMeanBetaAmp12	82	mMeanTotalAmp7
3	pBetaPower	23	pMeanAlphaAmp5	43	mMeanAlphaAmp18	63	mMeanBetaAmp13	83	mMeanTotalAmp8
4	mBetaPower	24	pMeanAlphaAmp6	44	pMeanBetaAmp1	64	mMeanBetaAmp14	84	mMeanTotalAmp9
5	pTotalPower	25	pMeanAlphaAmp7	45	pMeanBetaAmp2	65	mMeanBetaAmp15	85	mMeanTotalAmp10
6	mTotalPower	26	mMeanAlphaAmp1	46	pMeanBetaAmp3	66	mMeanBetaAmp16	86	mMeanTotalAmp11
7	pAlphaDomFreq	27	mMeanAlphaAmp2	47	pMeanBetaAmp4	67	mMeanBetaAmp17	87	mMeanTotalAmp12
8	mAlphaDomFreq	28	mMeanAlphaAmp3	48	pMeanBetaAmp5	68	mMeanBetaAmp18	88	mMeanTotalAmp13
9	pBetaDomFreq	29	mMeanAlphaAmp4	49	pMeanBetaAmp6	69	pMeanTotalAmp1	89	mMeanTotalAmp14
10	mBetaDomFreq	30	mMeanAlphaAmp5	50	pMeanBetaAmp7	70	pMeanTotalAmp2	90	mMeanTotalAmp15
11	pTotalDomFreq	31	mMeanAlphaAmp6	51	mMeanBetaAmp1	71	pMeanTotalAmp3	91	mMeanTotalAmp16
12	mTotalDomFreq	32	mMeanAlphaAmp7	52	mMeanBetaAmp2	72	pMeanTotalAmp4	92	mMeanTotalAmp17
13	pAlphaVar	33	mMeanAlphaAmp8	53	mMeanBetaAmp3	73	pMeanTotalAmp5	93	mMeanTotalAmp18
14	mAlphaVar	34	mMeanAlphaAmp9	54	mMeanBetaAmp4	74	pMeanTotalAmp6		
15	pBetaVar	35	mMeanAlphaAmp10	55	mMeanBetaAmp5	75	pMeanTotalAmp7		
16	mBetaVar	36	mMeanAlphaAmp11	56	mMeanBetaAmp6	76	mMeanTotalAmp1		
17	pTotalVar	37	mMeanAlphaAmp12	57	mMeanBetaAmp7	77	mMeanTotalAmp2		
18	mTotalVar	38	mMeanAlphaAmp13	58	mMeanBetaAmp8	78	mMeanTotalAmp3		
19	pMeanAlphaAmp1	39	mMeanAlphaAmp14	59	mMeanBetaAmp9	79	mMeanTotalAmp4		
20	pMeanAlphaAmp2	40	mMeanAlphaAmp15	60	mMeanBetaAmp10	80	mMeanTotalAmp5		

The dispersion within a cluster is calculated from:

$$S_i = \left\{ \frac{1}{T_i} \sum_{j=1}^{Ti} \left\| x_j - a_i \right\|_2^q \right\}^{\frac{1}{q}},$$

where a_i is the centroid of cluster i and T_i is the number of points in the same cluster. q =2 in our case (i.e., S_i is the standard deviation of the Euclidean distance between all data points in a cluster and the cluster's centroid)

The DBI is then calculated as follows:

$$DBI \equiv \frac{1}{N} \sum_{I=1}^{N} R_I ,$$

where $R_I \equiv \text{maximum of } R_{ij} \; i \neq j$, and *N* is the number of classes (4 in our case).

The centroid locations for each cluster were hereby calculated by simple averaging of a feature's values for a particular class. Note: smaller DBI values indicate less cluster overlap and thus better expected class separation.

Finally, to further magnify the differences between suitable and unsuitable feature/channel configurations, the DBI values were raised to the power of 1/2, heretofore called the *modified DBI* (MDBI).

III. RESULTS AND DISCUSSION

Fig. 1 shows a representation of the relative MDBI magnitudes for all 28 channels and 93 features. Darker values indicate smaller MDBIs. At first glance it appears that the smallest values (darker areas = better class separation) are not biased towards motor channels or those nearby. To investigate whether such bias may exist, the MDBI matrix was split into motor and non-motor channels.

Motor channels were chosen as the ones that were closest to the physiological area of interest for wrist movements. These were: FC1, FC5, C5, CP5, FC2, CP3, CPZ, CZ, CP1, C1, C3, FCZ, C2, FC3 and CP2.

The *non-motor channels* were thus the following: F1, F5, PZ, P1, P5, P7, P3, TP7, FZ, P2, T7, FT7 and F3.

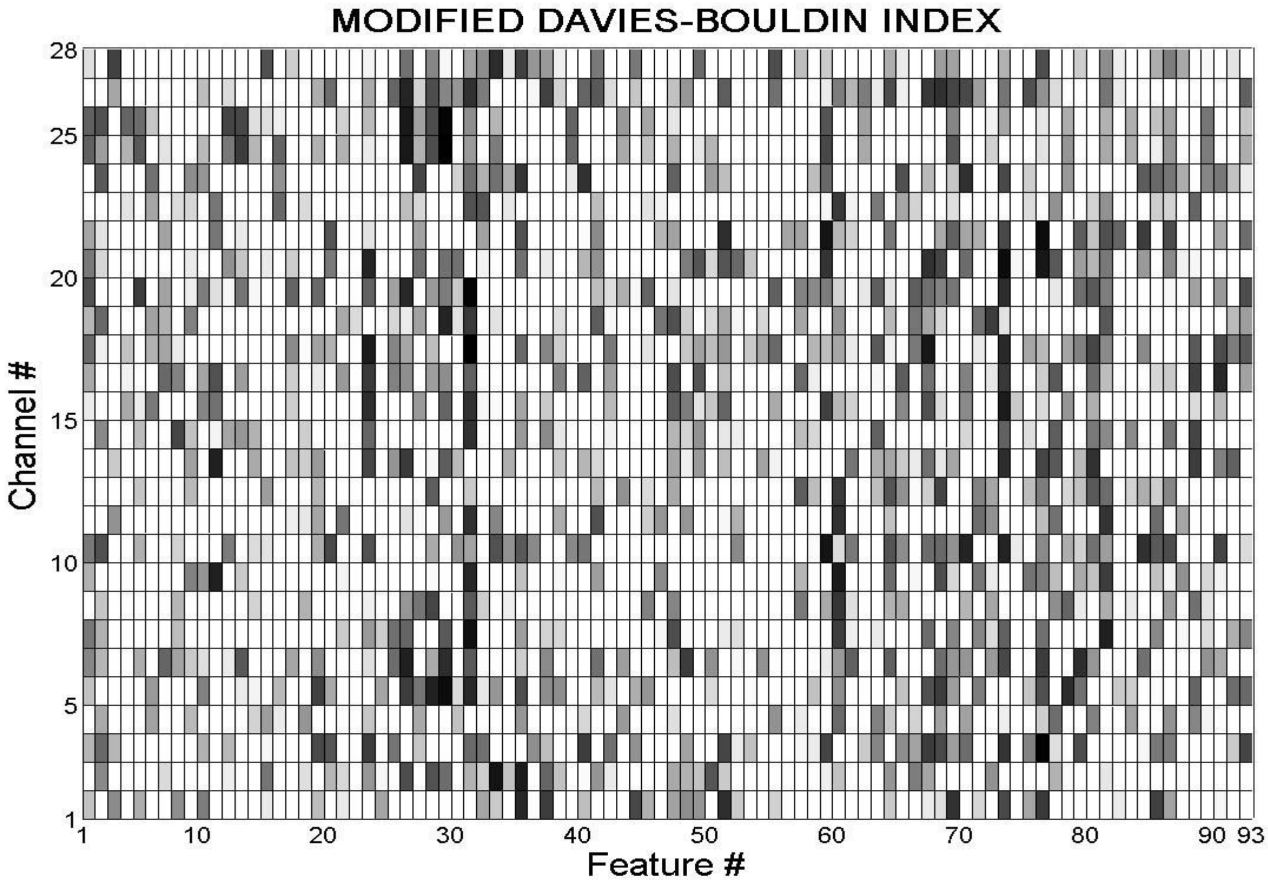

Fig. 1 – MDBI values for all channels and features.

Fig. 2 shows the distribution of MDBI values for (a) motor and (b) for non-motor channels. It can be seen that the distributions are very similar. When only the best 5% of all values for each channel type (motor vs. non-motor) were extracted for further analysis, the following results were obtained:

- Mean motor channels MDBI: 2.44 (stdev=0.14) (calculated using 69 MDBI values)
- Mean non-motor channels MDBI: 2.42 (stdev=0.13) (calculated using 60 DBI values)
- Kurtosis behavior of the 'best 5%' MDBI distributions led to acceptance of normality in the distributions. Thus, a z-test was run to determine whether the motor and the non-motor samples belonged to the same population.
- The null hypothesis H_o could not be rejected at α=0.05.

Table III lists the 10 best combinations of channels and features based on the MDBI values. For comparison purposes, the largest MDBIs were in excess of 280.0.

One of the interesting results shown in Table III is the presence of several non-motor channels, including channel T7 (with feature 29), which yielded the lowest MDBI, and hence the best class separation, although several other values are so close they should be considered to be equal for pattern recognition purposes. The presence of three non-motor channels among channels among the best ten channel/feature configurations listed, does give a clear indication that more attention should be given to non-motor locations even when the task under investigation is movement related.

TABLE III
RELATIVE CLASS OVERLAP FOR THE BEST FEATURE-CHANNEL CONFIGURATIONS

MDBI Value	Channel, Feature	Channel Type
2.59	T7, 29	non-motor
2.60	C1, 31	motor
2.64	C3, 31	motor
2.65	FT7, 29	non-motor
2.70	FCZ, 59	motor
2.70	FC1, 76	motor
2.70	CP5, 31	motor
2.72	FZ, 59	non-motor
2.75	FCZ, 73	motor
2.76	FCZ, 29	motor

Also, notice that feature 29 (mMeanAlphaAmp4) yielded 3 of the 10 best MDBI values. This means that good class separation can be obtained from such a simple feature as the alpha band amplitude data from 550 to 650ms (including the 250ms removed window) and from 750 to 850ms after the visual stimulus was given. In other words, results from this study show that the more computationally expensive frequency domain features may not always lead to better class separation (and hence easier classification).

V. CONCLUSION

EEG data class separation was investigated for four wrist movement classes using a 28 channel setup and the Davies-Bouldin Index. Many of the channels that yielded the best theoretical movement class separation were channels that were far from the motor areas of interest. While the study had restrictions that preclude further generalization of our conclusions (i.e., saccadic interference removal and single subject protocol), results do suggest more attention should be given to non-motor locations when investigating movement related intentions within referential EEG recordings.

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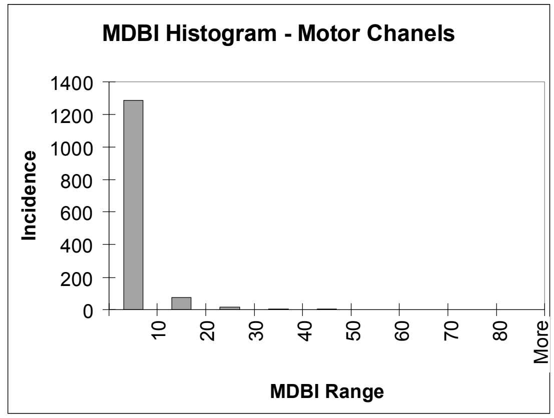
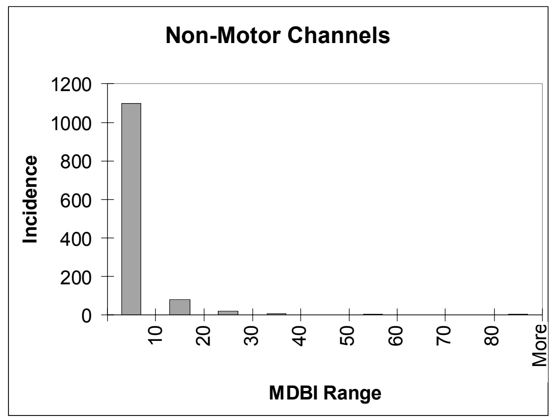


(a)



(b)

Figure 2 – MDBI values distribution for motor (a) and non-motor (b) channels.