1st Order Class Separability using EEG-Based Features for Classification of Wrist Movements with Direction Selectivity

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Abstract — **28 channel EEG data were recorded while a subject performed wrist movements in four directions. Four feature types were extracted for each channel following optimized filtering of the signals. 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 a first order histogram approach. The best feature/channel configurations contained channels both that were close and far from motor areas. While the scope and depth of the study was very limited, the results do suggest more attention should be paid to non-motor areas when investigating movement related EEG.**

Keywords — **Brain-Computer Interface, Movement Related Potentials, Pattern Recognition, EEG**

I. Introduction

Much research into the detection of motion related potentials (MRPs) in electroencephalogram (EEG) data for use in brain- computer interface (BCI) systems has focused of differentiating between movements in different limbs, such as right vs. left hand movement [1]. This has advantages because discriminating activity in the brain is likely to occur in different locations, thus allowing for easier classification. However, in this study, the possibility of detecting intentions in one limb was investigated with the class relating to direction of movement.

The ability to successfully classify MRPs into direction related groups would be useful as it could produce a number of control options in a single trial. Increasing the control options would increase the available bandwidth of the BCI system. Furthermore when used to control a mouse cursor or prosthesis, using direction-selective intentions for control may make the system feel more natural to use than systems using intentions related to more distal limbs.

This study focused on right-side wrist movements. Several features for each of 28 channels were used as a starting feature set. At this stage, a histogram-based analysis was applied to all features to determine which combination of feature and channel yielded the best class separability.

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™ Symamp system with the electrodes positioned according to the standard 10-20 system. 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. The data consisted of a series of repeated movement trials initiated by audio and visual cues. The subject looked at an X Y plot of wrist position. 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., extention 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 encompass the alpha band, 12-32Hz to encompass the beta band, and 5Hz-32Hz to encompass 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 ratio for the various bands of interest.

B. Feature Extraction

Two signal segment types were then extracted from each trial for further analysis. The segments related to the planning and the movement execution stages, respectively, of each trial as these may produce different features. The first segment contained data following the visual clue, 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 [2]. 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.

The second segment contained data starting at the first audio stimulus, with a delay of 100ms to account for any 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.

The following features 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. This produced a total of 2604 feature values for each trial.

C. Feature Selection and Class Separability

In order to decide which of the various features and channels would be of most use in classification using the simplest of approaches (more complex approaches are underway), a 1st order statistical method for evaluating their usefulness was devised, as follows. The statistical frequency histograms for each feature (not to be confused with the signal's frequency domain representation) in a given class were produced, with each bin containing 10% of the total global (i.e., for all classes) range for that feature. There were four classes, each relating to an up, down, left or right movement. The four histograms were then superimposed on each other. The total area of the overlaid histograms was calculated, as well as the area over which they overlapped. This was calculated using a spline fit for each histogram and subsequent integration under the curve. The relative area overlap between all four classes was then estimated for each feature *i* and channel *ch* using the following overlap measure:

$$RAOverlap_{i,ch} = \frac{Total\ class\ overlap\ area_{i,ch}}{Total\ histogram\ area_{i,ch}} \ .$$

The relative class overlap area was then used as a measure of the class separability for each feature and channel. The lowest *RAOverlap* values and those within 10% of that value (as measured using the entire global range for a given feature and channel) are listed in Table I below. The smallest value indicates the best class separation.

III. Results and Discussion

Table I lists the best combination of channels and features based on the RAOverlap values. The largest overlap values, not shown, were near 1.0.

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

Feature	Channel	Band	Segment	RAOverlap
Power	C5	Alpha	Movement	0.46
Mean amplitude 615ms-715ms after stimulus	Cz	Alpha	Planning	0.48
Mean amplitude 1.3sec-1.4sec after stimulus	Cz	Beta	Movement	0.48
Dominant frequency	P5	Total	Planning	0.49
Mean amplitude 400ms-500ms after stimulus	CP5	Alpha	Movement	0.50
Mean amplitude 400-500ms after stimulus	TP7	Alpha	Movement	0.51
Mean amplitude 215ms-315ms after stimulus	FC5	Total	Planning	0.52

One of the interesting results shown in Table I is the predominance of non-motor channels. This is not a complete surprise given that the setup included many more non-motor channels than motor ones. However, the closeness between class separation values for all channels listed, irrespective of their location or feature type, does give a strong indication that more attention should be given to non-motor locations even when the task under investigation is movement related.

V. Conclusion

EEG data class separation was investigated for four wrist movement classes using a 28 channel setup. Many of the channels that yielded the best theoretical movement classification were channels that are far from motor areas. While the study employed only some of the simplest features and statistical techniques available, results do suggest more attention should be given to non-motor locations when investigating movement related intentions within referential EEG recordings.

REFERENCES

[1] E. Yom-Tov, G. F. Inbar, "Feature Selection for the Classification of Movements from Single Movement-Related Potentials". *IEEE Trans Neur Sys Rehab Engr.*, Vol. 10(3):170 – 177, 2002.
[2] S. Gezeck, J. Timmer, "Detecting multimodality in saccadic reaction time distributions in gap and overlap tasks". *Biol. Cybern.,* Vol. 78(4):293-305, 1998.

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