DISTINCTION SENSITIVE LEARNING VECTOR QUANTIZATION (DSLVQ) - APPLICATION AS A CLASSIFIER BASED FEATURE SELECTION METHOD FOR A BRAIN COMPUTER INTERFACE [1]

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ABSTRACT

This paper describes a simple but very powerful method for feature selection. The Destinction Sensitve Learning Vector Quantizer (DSLVQ) is a learning classifier, which focuses on relevant features according to its own, instance based classifications. Two different experiments describe the application of DSLVQ as a feature selector for an EEG-based Brain Computer Interface (BCI) system. It is shown that optimal electrode positions as well as frequency bands are strongly dependent on each subject and that a subject specific feature selection is very important for BCI systems.

INTRODUCTION

For the construction of an Electroencephalogram (EEG)-based Brain Computer Interface (BCI) to help people with severe motor impairment (13), (7) it is necessary to classify spatiotemporal EEG patterns related to specific "thoughts" on-line. These EEG patterns are recorded on the intact scalp during pure mental activity and can be classified with a learning classification method which is able to adapt to each specific subject. The classification results of the classifier can then be used to generate control signals for different tasks. The number of available features is considerable: in practice the number of electrodes for EEG recording can be high (up to 30 and more) and different frequency bands can be used for classification. However, the number of examples which can be recorded from one subject is limited. Since the number of examples which are necessary to train a learning classifier properly generally increases with the complexity and dimensionality of the classification problem, it is important to pre-select the most distinct features or feature combinations. Flotzinger et al. (2) and Pregenzer et al. (10) demonstrate that selection of appropriate features can improve the performance of a BCI considerably. Pfurtscheller et al. (8) show that the Distinction Sensitive Learning Vector Quantizer (DSLVQ, (9), (11)) is an appropriate tool for single trial based data analyses. In this study two different experiments are used to show that DSLVQ is an appropriate feature selector for a BCI: the first experiment employs DSLVQ to select the most distinct electrode positions from a large number of possible positions. The second experiment uses DSLVQ to analyze the importance of 1-Hz bands of EEG power spectra for the prediction of three different types of movement. This experiment shows for the first time that for prediction of the type of movements from EEG recordings, the optimal frequency bands are strongly dependent on the subject.

DISTINCTION SENSITIVE LEARNING VECTOR QUANITZATION (DSLVQ)

The Learning Vector Quantizer (LVQ, (4)) is a learning classifier. Its classification is based on a number of instances (codebook vectors): the closest codebook vector to an unknown example is used to determine its class membership. The goal of the LVQ learning algorithm is to find an optimal distribution of its codebook vectors in the n-dimensional vector space. Flotzinger et al. (1), (3) show that LVQ is a very powerful classifier for single trial EEG data. Compared with other methods such as Backpropagation Neural Networks (12) one major advantage of the LVQ classifier is its good generalization ability (5).

The Distinction Sensitive Learning Vector Quantizer (DSLVQ, (9), (11)) is a modification of LVQ: it employs a weighted distance function where the influence of single feature distances is not equal:

$$\mathrm{DSdist}(\mathbf{x},\mathbf{y},\mathbf{w}) = \sqrt{\sum_{n=1}^{N} (\max(0, w_n)(x_n - y_n))^2}$$

The difference between the DSLVQ and the LVQ distance function is the implicit scaling with DSLVQ. The algorithm estimates optimal scaling factors (weights) for every dimension, in parallel to the codebook positions, through a second learning process. This learning process optimizes a weights vector $w=(w_1,w_2,...,w_N)$ where each weight value w_n holds the informative value of feature n. More informative features and feature combinations gain more influence on the classification. The iterative learning rule for the weights is based on observations from classifications: if, during a training iteration t, feature n is found relevant for the correct classification of the training example $\boldsymbol{x}(t)$, w_n is increased; if it inhibits a correct classification of $\boldsymbol{x}(t)$, w_n is decreased.

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The following learning rule is employed for a weights learning iteration t:

$$\mathbf{w}(t+1) = \mathrm{norm}(\mathbf{w}(t) + \alpha(t)(\mathrm{norm}(\mathbf{nw}(t)) - \mathbf{w}(t)))$$

It shifts the present weights vector $\boldsymbol{w}(t)$ towards a new weights vector $\boldsymbol{nw}(t)$. The learning factor $\alpha(t)$ determines the influence of training iteration t. If a quite small number of training examples is repeatedly presented to the classifier, $\alpha(t)$ should decrease gradually to zero from an initial value $\alpha(0)$ such as 0.05. The weights vector $\boldsymbol{nw}(t)$ is obtained from the present classification: Let $\boldsymbol{m}_c$ be the closest codebook vector from the correct class and $\boldsymbol{m}_o$ the closest codebook vector from a different class. The new weights vector $\boldsymbol{nw}$ can then be calculated as:

$$nw_n(t) = \frac{d_{o_n}(t) - d_{c_n}(t)}{\max(d_{o_n}(t), d_{c_n}(t))}$$

Here d_{c_n} and d_{o_n} is the single feature distance of the n^{th} feature value of the training example $x(t)$ and the corresponding value of the codebook vector $\boldsymbol{m}_c(t)$ and $\boldsymbol{m}_o(t)$, respectively.

Normalization of the present as well as the new weights vector (e.g. to unit length) inhibits that the influence of a training example is dependent on its distance from the decision border. Without normalization, examples close to one of the decision borders would have smaller weights for all the features, i.e a short new weights vector. The interesting information is, however, the direction of the new weights vector rather than its length. In other words: the weights must be updated with relevance differences among the features observed at the present classifcation rather than with a quality measurement for this classification.

An interesting question, which is also discussed in (11), is when the DSLVQ weights updating rule applies: the LVQ3 training algorithm (4) for the codebook vectors concentrates on the decision borders: LVQ3 focuses on cases where only one of the two closest codebook vectors belons to the correct class and the training example $\boldsymbol{x(t)}$ lies within a small area (window) around the midplane of these codebook vectors. However, codebook learning and weights learning are not identical. Especially when the number of training examples is small or when the weights are used for data analyses and feature selection it is not optimal to focus only on a small subset of examples which are lying close to the decision borders. Therefore, this study considers also cases where $\boldsymbol{x(t)}$ is not lying inside the window. Furthermore, cases where the two closest codebook vectors are from the same class, which have only minor influence on the codebook learning, have stronger influence on the weights learning.

The trained weights vector $\boldsymbol{w}$ of DSLVQ gives an insight into the LVQ classifier. It shows which features and feature combinations are important for the classification problem. This study uses the DSLVQ weights for feature selection: a low weight value indicates that the feature is not important for the BCI system and that it may be dropped.

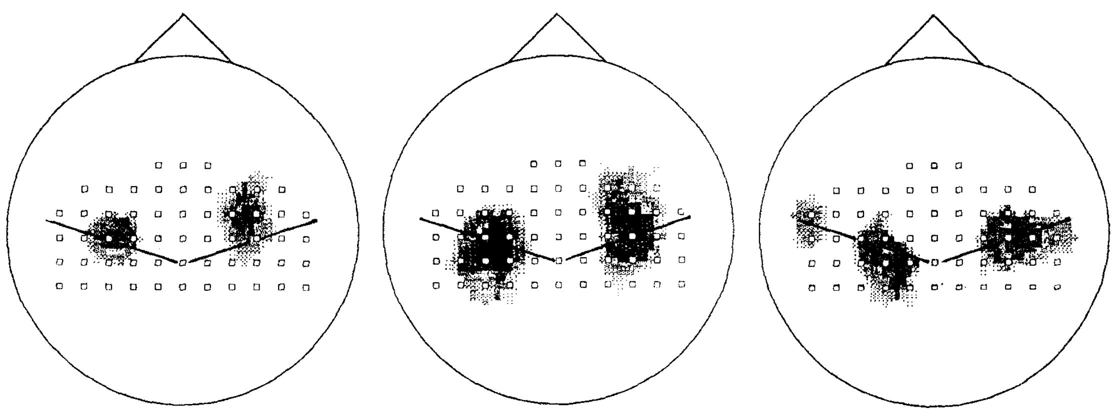

Figure 1: Schematic view of the head with the nose above and electrode positions arranged in distances of 25 mm. The average weight values of the DSLVQ classifier are linearly interpolated for three subjects (a4,b6,b8). "Black" indicates areas important for discrimination between preparation of left and right hand movement. Scale in arbitrary units.

EXPERIMENTAL RESULTS

In the following BCI experiments movement has to be predicted from EEG recordings prior to movement onset. The experimental paradigm for data recording and processing of the first experiment will be described here in more detail: a subject is seated in a darkened room in front of a computer screen. After an acoustic warning stimulus, a cue on the screen indicates to the subject which hand should be used to press a microswitch. One second later, another stimulus (RS) indicates that the movement should start. On average, movement was initiated about 0.5 seconds after RS. EEGs are recorded with 56 scalp-electrodes placed with an inter-electrode distance of 2.5 cm over relevant areas of the scalp (SMA, motor and somatosensory areas; the exact electrode positions are indicated in figure 1). EEG was sampled at 128 Hz, digitally band pass filtered from 10-12 Hz, then squared and compressed to 1 sample per second. For classification one-second periods (one sample per channel) before movement onset were used. Patterns with strong artifacts, which may be caused for example by eye-movements, were discarded. After this selection beween 76 and 156 patterns were available for each subject. The information, which is exploited for classification, is the amplitude attenuation or event-related desynchronisation (ERD) of characteristic frequencies which can be observed at specific locations before certain movements. DSLVQ is applied to the 56-dimensional data vectors, where each feature value correspondes to one electrode position. Figure 1 shows average DSLVQ weight values from 10 runs of the DSLVQ classifier. Averaging over multiple runs of DSLVQ with different initialization values and training sequences reveals more reliable weight values. For all three subjects the outlined electrode positions yform areas over the left and right primary sensorimotor hand regions. This is highly reasonable and verifies the DSLVQ selection. It is important to note that the selected areas are, however, not identical for all three subjects: the exact locations of the most important electrodes are dependent on the individual subject.

In the second experiment three different types of movement (left hand, right hand and foot) have to be discriminated. Three bipolar EEG signals are recorded from sensorimotor areas. After calculation of power spectra from a one second period before movement, 1-Hz bands from 5 to 24 Hz are analyzed separately. DSLVQ is employed to select the most relevant frequency bands. Figure 2 shows the DSLVQ weight values from 4 different subjects. The reported values are average weight values from 10 runs of DSLVQ and all 3 positions. For all the subjects the significance of mu rhythms from 10 to 12 Hz can be seen clearly. However, similarly to the results of the first experiment, an optimal feature selection is strongly

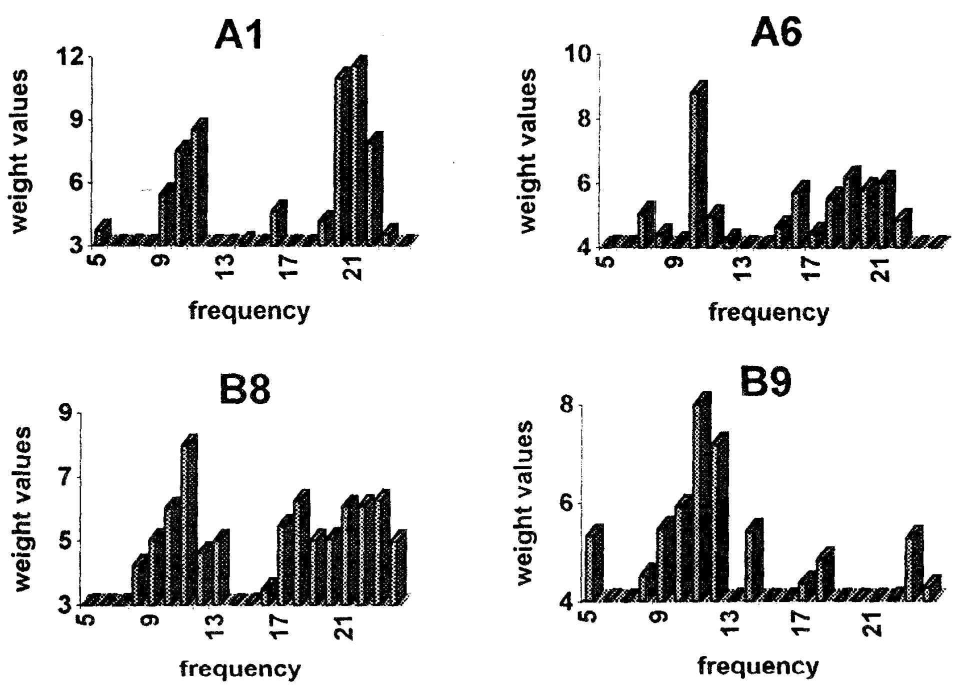

Figure 2: Average DSLVQ weight values for 1-Hz spectral bands from 5 to 24 Hz; 4 different subjects (A1,A6,B8,B9). High relevance for the discrimination of the type of a planned movement is reflected in high weight values.

dependent on each individual subject. Notable differences between the 4 subjects are: a significance of lower mu rhythms (8-10Hz) can only be observed for two subjects and the relevance of the central beta rhythms (20-23Hz) varies strongly: while central beta rhythms are even more informative than mu rhythms for one subject (A1), they are not relevant at all for another subject (B9).

CONCLUSION

Single trial EEGs can be used to predict different types of movement. One problem for a learning classifier is the huge number of possible features such as different electrode positions and frequency bands. The results from two independent experiments show significant relevance differences among these features. However, the most important electrode positions and frequency bands are not identical for different subjects. Therefore, it is necessary to select the features individually for each subject. DSLVQ is a classifier which selects a sub-set of optimal features for a classification problem to optimize its instance based decisions. It is shown that DSLVQ can be employed as a simple but very powerful feature selection method for single-trial EEG data. Compared with other feature selection methods such as genetic algorithms, one major advantage of DSLVQ is its speed (2). Compared with averaging methods for EEG data analyses such as ERD mapping (6), which has also been applied for feature selection, a major advantage of DSLVQ is that it is based on single trials (8). Averaging weight values from different runs of DSLVQ, where different initial values and training sequences can be used, improves the reliability of the DSLVQ feature selection. This is one reason why feature selection is still important even if DSVLQ is also used as the subsequent classifier.

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