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# Electrocorticographic signal classification based on time-frequency decomposition and nonparametric statistical modeling

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***Abstract*— In this paper, we propose a novel statistical framework based on time-frequency decomposition and nonparametric modelling of electrocortial (ECoG) signals in the context of a Brain Computer Interface. The proposed method decomposes the ECoG signals into subbands (with no down-sampling) using Gabor filters. The subband signals are then encoded using a nonparametric statistical modeling and the distance between the resulting empirical distributions is as used as the classification criterion. Cross-validation experiments were carried out to pre-select the channel (from the multi-channel sources) and subbands which can archive the best classification scores. The proposed framework has been evaluated using Data Set I from the BCI Competition III and results indicate a superiority over conventional vector quantization method particularly when the number of training samples is small. It was found that the proposed nonparametric distribution modeling based on empirical inverse cumulative distribution distance is fast, robust and applicable to the mobile systems.**

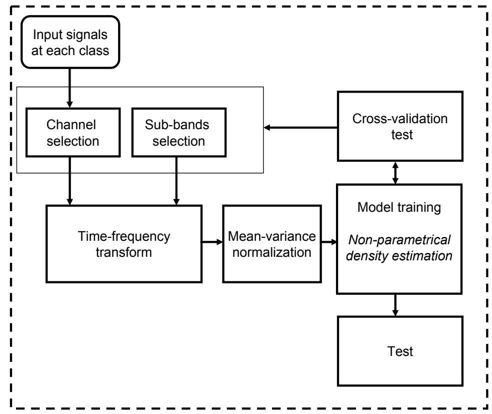


Fig. 1. Block diagram of signal flow.

## I. INTRODUCTION

BRAIN activity produces electrical signals that can be detected from the scalp, from the cortical surface, or from within the brain. One primary goal of Brain Computer Interface (BCI) research is to infer the meaning of such signals in order to construct an interface to assist paralyzed patients in, for example, expressing their wishes, operating a word-processor, or even control multidimensional movements of a robotic arm or a neuroprosthesis [1]-[2].

BCIs can be noninvasive or invasive. Among the noninvasive methods, EEG-based BCI is more frequently studied. While some EEG-based prototypes are already in use for some basic communication and control purposes, the performance of EEG-based BCI suffers from the typically very low signal-to-noise level [1]. Invasive BCI, on the other hand, using the electrocorticographic signal (ECoG) from the cortical surface, is an alternative which is believed to overcome many of the problems present in EEG signals [3]-[5]. However, although preliminary results suggest the feasibility of ECoG-based BCIs, a number of questions remain. In particular, it is recognized that the conventional methods applicable to EEG are not ideal for ECoG signals [6]. Recently, some good algorithms for processing of ECoG were proposed in the BCI Competition III [7]. These algorithms are mainly based on a combination of conventional feature-set and Support Vector Machine (SVM) for classification. While some algorithms achieved relative high identification scores, it is difficult to explain the real reason of getting these results. From the authors' point of view, it is difficult to generalize such methods into a framework for ECoG signal processing.

In this work, we propose a novel framework for ECoG signal processing, where the sample signal is encoded using the time-frequency decomposition and non-parametric statistical modeling. The main points of our system is follows. First, we propose an adaptable Gabor-filter system, enabling to fit the best bandpass for each classification task. Second, we do not adopt down-sample in suband decompositions and therefore could accurately estimate the statistical distributions even with single sample. Third, we develop a novel non-parametric nonparametric distribution modeling based on empirical inverse cumulative distribution, which was found to be fast, robust and applicable to the mobile systems. The classification was carried out on the encoded parameters. Both Euclidean distance and SVM methods were investigated.

The organization of this paper is as follows. We briefly review the system architecture in Sec. II, followed by a description of the time-frequency decomposition and non-parametric modeling in Sec. III and Sec. IV respectively. Discussion of the experimental results and a comparison of proposed methods are presented in Sec. V. Finally, we provide some concluding remarks in Sec. VI.

## II. SYSTEM OVERVIEW

The block diagram for the proposed signal processing is illustrated in Fig. 1. The signal from each ECoG channel is transformed into the time-frequency domain then the "preferred"[1] subbands are normalized to have zero-mean and

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[1]The pre-selection determined by a set of cross-validation experiments, outlined shortly in Sec. V-B.

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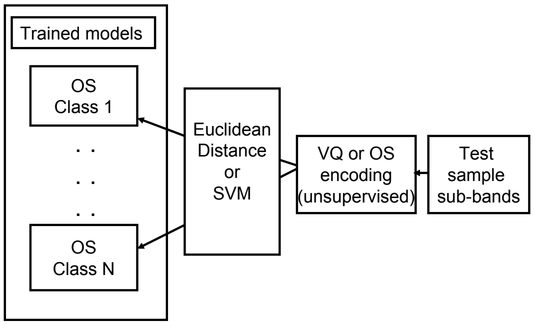

Fig. 2. Proposed non-parametric statistical encoding and testing.

unit variance. This normalization is required to remove the DC bias due to the recording procedure. The normalized subbands are encoded using the nonparametric modeling. Two methods of vector quantization (VQ) and empirical inverse cumulative distribution function (CDF) are developed. Two classification method using Euclidean Distance (ED) on empirical distributions and SVM were investigated. For the ED-methods, the VQ or inverse CDF models are trained on the whole training dataset and the Euclidean Distance between encoded parameters from each test sample to the trained models were calculated in order to classify the object. For the SVM-methods, the signals in both training and testing are encoded. Then the SVM classification is carried out on the encoded parameters. Cross-validation was performed to optimally determine the channel and the subbands to use for subsequent classification. The rationale is that since ECoG signal is known to be extremely localized, only one channel is selected. The schematic diagram of this approach is shown in Fig. 2.

## III. Time-frequency decomposition

Conventional time-frequency techniques which have been used for BCI applications use either bandpass filters or wavelet decomposition. The bandpass filters decompose the brain signals into certain subbands, namely the delta, theta, mu, alpha and beta bands [1], which are shown to have specific behaviours for different types of motor imagery applications. However, in the real situations, these subbands can exhibit large fluctuations from person to person and therefore the use of fixed band-pass filters are not optimal. On the other hand, the conventional use of wavelet transform is to recovery only the signal's spectrum and therefore the pyramid subband structure with down-sampling are adopted.

In this work, we proposed to represent the ECoG signals by their subband distributions rather than the spectrum. Consequently a full-time resolution should be used. Moreover, for the classification task, it is unnecessary for the filterband system to be orthogonal in order to recover the source signal. In view of such considerations, we adopt a Gabor filter system rather than conventional wavelet transform. The Gabor filter [8] was chosen as an adaptable bandpass filter system, whose impulse response is defined by a harmonic function multiplied by a Gaussian function

$$h(t, f_0, \sigma) = \frac{\sigma}{\sqrt{2\pi}} \exp\left(-\frac{\sigma^2 t^2}{2} + j2\pi f_0 t\right). \tag{1}$$

The frequency response of a Gabor filter is a Gaussian centered at $f_0$

$$H(f, f_0, \sigma) = \exp\left(-\frac{2\pi^2 (f - f_0)^2}{\sigma^2}\right) \tag{2}$$

with the bandwidth proportional to $\sigma$. In the proposed method, a filterbank system consisting of Gabor filters with various bandwidths is convolved with the input signal, resulting in a time-frequency decomposition. Linear frequency scale is used, with the number of filters and the respective bandwidths experimentally chosen.

## IV. Non-parametric subband distribution modeling

### A. Vector quantization and Euclidean-distance based classification

Vector quantization can be regarded as a simple method to approximate the subband distributions by a small set of discrete points, the so-called codebook. The most common criterion for determining the codebook and partitions is to minimize the average total distortion on the training data. For this paper, VQ was implemented using the iterative LBQ algorithm [9]. Given a trained codebook, a classification score is defined as the minimum of the average distortion of a given test sequence to the set of code vectors.

### B. Order statistics and empirical inverse cumulative distribution function

An alternative way to model the subband distribution is to fit its cumulative distribution function (CDF). The CDF satisfies monotonicity property and is less sensitive to errors in fitting compared to the probability density function. In the nonparametric approach, when the distribution distance should be used rather than likelihood ratio as a means of comparing distributions, the empirical CDF is preferred over conventional histograms. We will represent the subband distribution by the empirical inverse CDF, which is estimated using order statistics (OS), described as below.

Given a sample sequence in a subband $\{x_1, x_2, ..., x_M\}$ and the number $M$, the distribution of $x$ can be presented by a set of OS denoted by

$$c_i = x'_{q_i}, i = (1, 2, ..., M) \tag{3}$$

where

$$x'_1 \le x'_2 \le ... \le x'_M, \tag{4}$$

is the sorted sequence from $\{x_1, x_2, ..., x_M\}$ and

$$q_i = \left[ i\frac{M+1}{N} \right]. \tag{5}$$

The order statistics $c_i$ in (3) are in fact an empirical representation of the inverse cumulative distribution function

$$c_i = F_x^{-1}\left(\frac{i}{N}\right). \tag{6}$$

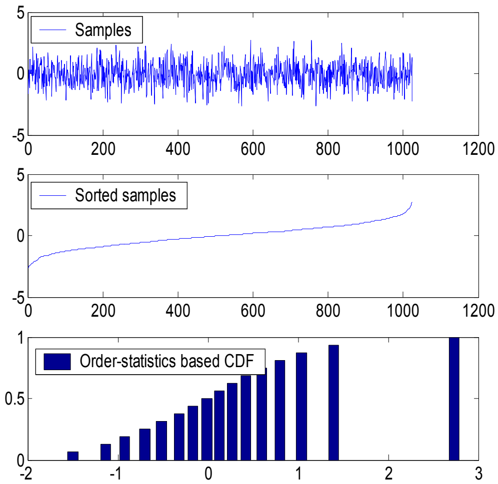


Fig. 3. Subband distribution representation by order statistics.

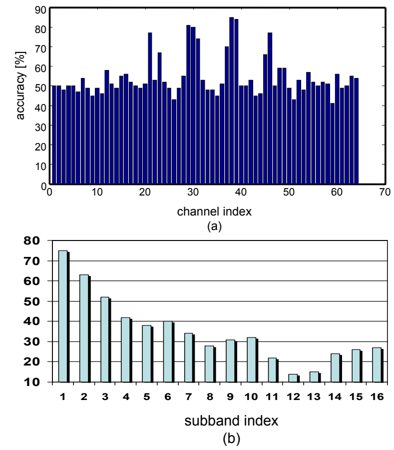


Fig. 4. Cross-validation evaluation (a) over channels (using full 8-subband system); (b) over subband (using 16-subband system).

Since the cumulative distribution is a monotonically increasing function, the set of its order statistics should fully represent the subband empirical distribution. The OS representation of subband distribution can also be regarded as an alternative to VQ but avoids the use of a codebook which contains very few samples. In addition, "noise subspace" due to non-attention and spikes can be partially removed from OS-codebook, i.e., only a confident set of

$$c_i = x'_q, i = (M_m, \ldots, M_s), \tag{7}$$

where $1 < M_m < M_s < N$, is used to represent the distribution. This is known as subspace justification.

Though the adaptive setting of $M_m, M_s$ is a very interesting challenge, we have decided to set these parameters experimentally in this paper. An example of subband output, sorted sequence, and CDF representation by OS is illustrated in Fig. 3.

## V. Experiments and Discussions

### A. Database

The proposed methods were evaluated using Dataset I [6] from the BCI Competition III [7]. This database contains ECoG recordings from two different sessions about one week apart, for cued motor imagery (left pinky, tongue) from one subject. During the BCI experiment, a subject had to perform imagined movements of either the left small finger or the tongue. The electrical brain activity signals were picked up during these trials using a 64 channel ECoG platinum electrode grid which was placed on the contralateral (right) motor cortex. Every trial consisted of either an imagined tongue or an imagined finger movement and was recorded for 3 seconds in duration. To avoid visually evoked potentials being reflected in the data, the recording intervals started 0.5 seconds after the visual cue had ended. The labeled training database contains 278 training trials and 100 test trials [7].

### B. System configuration optimization

Four methods, namely VQ-ED, OS-ED, VQ-SVM and OS-SVM, were implemented according to the names of the nonparametric statistical modeling and classification methods. For the SVM-method, a simple linear SVM machine is adopted [10]. A 4-fold cross-validation with 100-left-to-test samples was used to set the system configuration in the each part of following steps (one by one).

*1) Channel selection:* The preferred channels were selected by fixing the number of Gabor filters at 8, and using all of the subbands. As shown in Fig. 4 (a), which illustrates the classification accuracy with VQ-ED method, only few channels contain useful information while all others yield less than 50% accuracy. As a result, channel 38 is chosen for the remainder of experiments according to the best score in the identification. Note that, this channel is also found to be the best for all the methods.

*2) Filterbank system setting:* Next, given the fixed channel index, we verified that a 16 Gabor-filters, each with a bandwidth of $9.05Hz$ (i.e. $\sigma = 6.4$), is found to be the optimal choice.

*3) Statistical modeling:* For the VQ approach, the optimal codebook number was experimentally determined to be 8. For the OS method, the optimal number of OS to represent the subband cumulative distribution is found to be 16. The confidence interval for the OS-representation is experimentally found to be from indices 3 to 13.

*4) Subband selection:* Subband selection is a part of proposed scheme because through this process we can remove the non-informative or low signal-to-noise subbands which degrade the performance of the system. For this task, we evaluate the 16-filter system in cross-validation for each subband separately (see Fig. 4 (b)), then the subbands yielding the accuracy less than a threshold of 50% are removed. The remaining subband are gathered together. We verified that, for both systems, the first three subbands are most important and their combination is adopted in processing,

### C. Evaluation with different lengths of training database

Given the system configuration determined using procedures outlined in Sec. V-B, the proposed methods were then

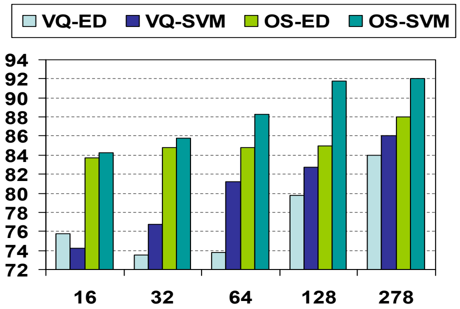


Fig. 5. Evaluation results, comparing the effects of using different number of training samples. The horizontal axis plots the number of trials used in training. The last column is when full training data set was used.

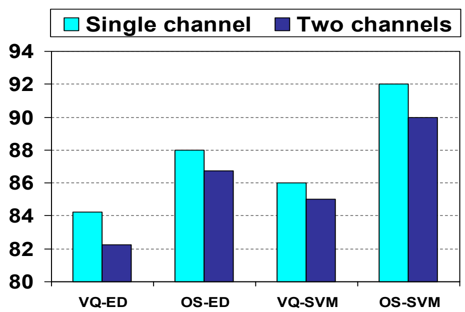


Fig. 6. Single channel/multichannel comparison

evaluated on the test using the full training data set. The results of this evaluation are shown in the last column in Fig. 5. The OS-SVM method is the best with 92% classification accuracy. This method also overcomes the best score on BCI III competition. The OS-methods in both cases overcome the VQ and this can be explained by the fact that the OS algorithm includes the subspace justification and can partially remove the unconfident components caused by un-attention or spike noise during the recording and therefore is more robust against noise. In next experiment, we evaluated the methods using fewer training samples because high accuracy while having a small training set is a practical requirement for ECoG-BCI approaches since the data collection is in general a difficult task. We perform the classification using 16, 32, 64, 128 trials, respectively. Similar to the cross validation test, 4-folds of the training set is randomly chosen and the evaluation result is averaged over training sets. The results are shown in Fig. 5. It can be seen that, the OS methods ares superior to the VQ in both cases and performs well even with 16 trials. The empirical inverse CDF is found to be suitable for the nonparametric subband distribution representation, particularly in the case of few samples.

### D. Single channel vs. multi-channel

In this section, we want to ask the interesting question: will combining signals from multiple channels improve the performance of the system compared to when only a single channel is used in the classification task? For multi-channel processing, we selected two best channels, according to their performances from the cross-validation test. It can be seen from Fig. 6 that the fusion of multi-channel signals in fact degraded the performance of system. This result seems to confirm the initial assumption that the ECoG signal is extremely localized and therefore there might be no additional benefits from a combination of signals from multiple channels.

## VI. Conclusions

In this paper, we have developed a statistical framework for the classification of ECoG signal for Brain Computer Interface. The main conclusions of this study are summarized as below:

1) The Gabor-filter system with full time-resolution is suitable for the statistical representation and analysis of the ECoG signals.
2) The proposed order-statistics encoding and SVM classification is recommended for the nonparametric approach since this method is robust, accurate and applicable for a mobile system.
3) The original assumption that the ECoG signal sources corresponding to certain motor imagery are extremely localized has been vindicated by the experimental results. The selection of a best channel based on training accuracy is simplest and most practical, which was confirmed in this study to be effective for the designated classification task.

## VII. Acknowledgments

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