A COMPARISON BETWEEN USING ECOG AND EEG FOR DIRECT BRAIN COMMUNICATION

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Abstract: Most brain-computer interfaces (BCIs) use the electroencephalogram (EEG) to measure brain activity. Alternatively, the electrocorticogram (ECoG) can be used, which provides better signal quality, but requires the implantation of subdural electrodes. Considering recent advances in signal processing, one might argue that employing modern spatial filters that can considerably improve signal quality and therefore the utility of EEG (as compared to ECoG), renders the ECoG unnecessary for BCIs. To investigate this, we applied spatial filtering methods to EEG and ECoG data for the discrimination between movement-related activity and background activity. From the results achieved, we cannot conclude that modern spatial filters make it possible to abandon invasive methods like ECoG in favour of EEG. Clearly, ECoG does have the disadvantage of being invasive, but our results show that significant gains remain possible by using this recording method.

Introduction

A brain-computer interface or direct brain interface is an assistive device that detects and interprets neural activity and translates this activity into computer commands [1]. The ultimate goal of such an interface is to provide effective communication without using the normal neuromuscular output pathways of the brain, but by accepting commands directly encoded in neurophysiological signals. For people suffering from locked-in syndrome, a medical state in which they have lost all voluntary muscle control, a BCI can be their only means of communication with their environment. Obviously, brain-computer communication is vital for people with such severe motor disabilities to increase their quality of life.

A variety of methods for recording brain activity might serve as the basis for direct brain-computer communication. The EEG is the most often used recording method, and although it is non-invasive and thus readily available, it has a number of disadvantages. These include poor signal-to-noise ratio, reduced spatial resolution, and susceptibility to artifacts, which are limiting factors for the performance of brain-computer interfaces. An alternative recording method is the ECoG, which has been used by far fewer research groups, primarily because it requires the implantation of subdural electrodes. The close proximity of the ECoG electrodes to the cortical surface, however, alleviates some of the limitations of the EEG. For instance, since there is less spatial summation and phase cancellation, brain activity at higher frequencies (gamma activity) can be recorded. These brain patterns, which are usually not present in the EEG, may be utilized to improve the detection rates of brain-computer interfaces [2]. Furthermore, artifact free signals can be relatively easily obtained with ECoG recordings.

Regardless of the type of signals utilized, direct brain to computer communication requires clearly distinguishable patterns of brain activity which can be identified by a computer system. Recent advances in signal processing have provided new powerful techniques (so called spatial filters) that can significantly improve the SNR of multi-variate signals. We combine these spatial filters with feature extraction and feature selection methods to improve the performance through a more stable representation or the removal of redundant or irrelevant information [3]. In fact, feature selection is necessary since the temporal and spatial distribution of patterns suitable for classification can vary between individuals – especially in ECoG data. A priori knowledge of most appropriate channel locations and features that describe the underlying patterns leading to optimal performance is seldom available. Consequently, feature selection methods are required to find an optimal feature set, or at least a good approximation therefore, for the classifcation task at hand.

In this work, we employ such techniques to discriminate between activity periods containing movement-related patterns and idling periods in EEG and ECoG recordings. By comparing the classification results, we attempt to assess the potential of ECoG recordings for direct brain-computer communication.

We chose to evaluate results involving classification of activity versus idling because it is more difficult than differentiating between two spatially distinct tasks such

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as left and right hand movement. Additionally, results produced from spatially distinct tasks are generally already very good leaving little room for improvement by the application of spatial filters. Furthermore, investigating this problem has important implications in the development of asynchronous (self-paced) BCI systems, where it becomes neccessary to differentiate between activity and idling [4]. Developing accurate methods to deal with this problem leads to the development of more natural easy to use interfaces since users can elicit commands to the system whenever they wish to. In other words, by focusing the study on differentiating between idle versus activity, the results were more appropriate for consideration of improvement with spatial filters and also provided useful insights for the development of asynchronous systems.

Although imagination of movement activates similar cortical areas and shares some similar temporal characteristics with the execution of the same movement [5, 6], it is important for the design of a practical BCI to ensure that a system developed using real movement does not rely on patterns which are more pronounced or more easily detectable than in movement imagery. Under this constraint, movement-related patterns can be employed for initial research on the development of a BCI, which is an advantage since they produce well-defined trigger signals that indicate their occurrence and provide a means to assess detection accuracy. Therefore, in this study, the investigation of the activity periods was limited to the time period no later than 0.5 sec after movement onset, where the patterns associated with real and imagined movement are known to be similar.

Materials and Methods

ECoG recordings of 6 subjects who participated in an epilepsy surgery program were used in this study. The subjects involved were either under evaluation or undergoing surgery for alleviation of intractable epilepsy. Up to 126 subdural electrodes were implanted on the surface of the cerebral cortex of each patient to record seizure activity and map cortical function. The 4 mm diameter electrodes were oriented in grids and strips, with a center-to-center distance of 1 cm [7]. Electrode palcement was selected solely for the purpose of the epilepsy monitoring without regards for BCI research, and electrodes were not necessarily located on motor cortex. The ECoG signals were recorded with a sampling rate of 200 (400) Hz and filtered between 0.05 and 100 (200) Hz. Each subject participated in short BCI research sessions, where they performed brisk middle finger movements in a self-paced manner with about 150 repetitions with resting (idling) periods of at least 6 seconds between successive repetitions.

The EEG data from six healthy subjects was recorded from a grid of 59 monopolar Ag/AgCl scalp electrodes referenced to the left mastoid. The closely spaced electrodes with distances of approximately 2.5 cm were placed in a configuration including the electrode positions C3, C4, Cz, Fz and Pz of the international 10–20 system. Figure 1 shows the positions of the electrodes. The EEG signals were filtered between 0.05 and 50 Hz with a sampling rate of 250 Hz.

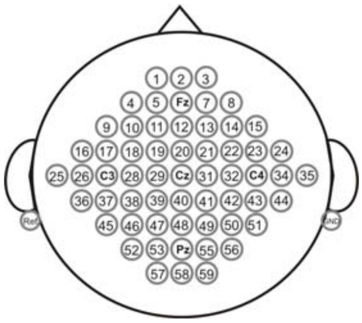

Figure 1: Positions of the 59 EEG electrodes used in this study. C3, C4, etc. indicate the corresponding locations of the international 10-20 system.

These subjects performed the same finger movement task as described above. The EEG signals were visually inspected for artifacts. Trials that contained artifacts were discarded from further analysis, which resulted again in datasets with up to 150 movements per subject. This was done to ensure that the performance differences between EEG and ECoG were not caused by artifacts in the EEG.

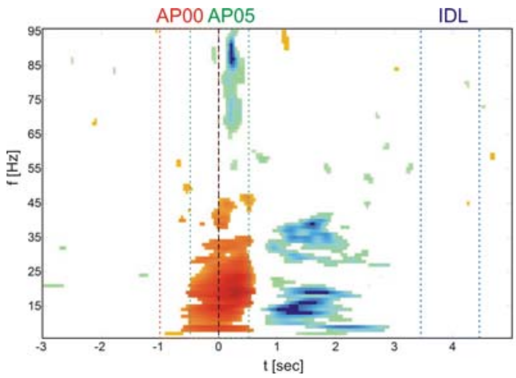

Figure 2: Time-frequency analysis of an ECoG channel showing ERD activity (red) and ERS activity (blue) and indicating activity and idling periods.

In order to compare EEG and ECoG data for BCI research, we defined a discrimination task between movement activity and idling (resting). For each trial, i.e. for each time frame around a movement, one idling and two activity periods were defined. The idling period (IDL) was defined as 3.5 to 4.5 sec after movement onset. The activity periods denoted as AP00 and AP05 were defined as -1 to 0 sec and -0.5 and 0.5 sec relative to movement onset, respectively. Figure 2 shows this timing on top of an ERD/ERS map calculated from ECoG data. ERD/ERS maps are time-frequency maps averaged over all trials that show statistically significant event-related desynchronization (decrease of band-power) and event-related synchronization (increase of

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bandpower) [8]. The doted vertical lines in Figure 2 indicate the two activity periods AP00 and AP05 and the idling period IDL, respectively. AP00 is the pre-movement period, which accounts for patterns associated with movement preparation. AP05 is the movement period, which contains ERD and ERS patterns assoicated with the actual movement. Clearly, the timing of the idling period was selected to avoid any overlapping with movement-related patterns (ERD or ERS).

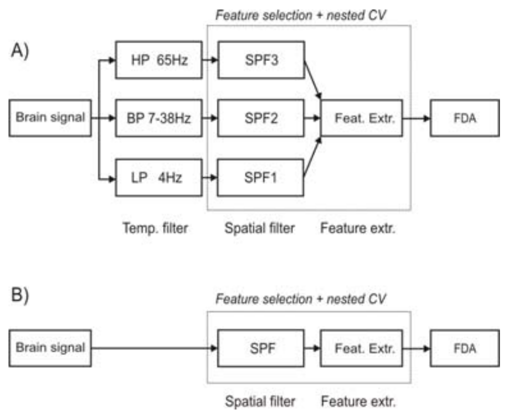

Figure 3: Schemes of the two different training procedures.

The offline analysis consisted of 4 processing blocks: pre-processing which included temporal and spatial filtering, feature extraction, feature selection, and classification. Further, the analysis was devided into a training and a testing step. The training sets consisted of 70% of the trials and the test set of 30% of the trials. In the training step, temporal filtering, the calculation of the spatial filters, feature extraction, the classifier set-up as well as feature selection was performed. In the testing step the spatial filter and a reduced feature set (found by the feature selection process) were used to produce the performance measure of the discrimination between movement- and idling patterns. Pre-processing included temporal and spatial filtering. The actual temporal filtering depended on the spatial filter applied.

Figure 3 depicts the two different schemes for training the system. Scheme A, which is similar to an approach suggested by Yong Li et al. [9], applies three different temporal filters derived by a Butterworth approximation where phase shifts were avoided by forward and backward filtering. This was only done on the training data. The approach used on the testing data was causal to ensure its suitablitily for online applications. This filtering yielded signals containing mainly delta, alpha/beta, and gamma activity, for which individual spatial filters were calculated. While all signals from all three bands were used for ECoG data, only signals of the two lower frequency bands were used in the case of EEG data, because of the reduced bandwidth of the EEG signals.

The spatial filters were derived from orthogonal source derivation (small Laplacian, LAP) [10], independent component analysis (ICA) [11], and common spatial patterns (CSP) [12]. There are a number of ICA algorithms available. In fact we investigated several popular ICA implementations including Sobi [13], FastICA [14], and Infomax [11]. Since all these ICA algorithms gave similar results and since Infomax has already been successfully applied to brain signals and also in BCI research [11], we only show results from Infomax in this paper. This algorithm was always applied in combination with principal component analysis (PCA), which reduced the number of dimensions from 59 channels to 16 components prior to ICA. Similarly, the first and last 4 common spatial patterns were selected, resulting in a reduced dimension of 8 per spatial filter. In the case of LAP and also for monopolar data (no spatial filter), the 16 channels showing the most prominent ERD/ERS activity (determined by the visual inspection of the corresponding ERD/ERS maps) were preselected prior to feature extraction. This reduction of channels and components respectively was done to simplify the feature selection process. Bandpower features from 4 Hz and 10 Hz bands as well as simple variance features as suggested in [12] were extracted from spatially filtered or the monopolar signals yielding feature spaces with a cardinality between 40 and 80. Table 1 gives an overview of the algorithms investigated, the number of preselected components/channels, and the number of extracted features for EEG and ECoG data.

Table 1: Spatial filters, applied training scheme, preselected components/channels, and number of extracted features.

Spatial Filter	Scheme	Comp./Ch.	Extracted Features ECoG	EEG
None	B	16	80	64
LAP	B	16	80	64
ICA	B	16	80	64
CSP	A	$3x8_{ECoG}$, $2x8_{EEG}$	64	40

In order to perform feature selection to reduce the dimensionality of the feature space down to an appropriate size for the training data available, the Sequential Floating Forward Selection (SFFS) method was used [15]. It is a heuristic search algorithm which starts with an empty feature set and subsequently tries to include and exclude single features from the already selected feature set until the performance measured by the fitness criterion stops increasing or a specified maximum number of features was selected. The selection criterion (fitness function) was based on the mean of the classification rate minus 1.5 times the standard deviation calculated from a 2x5 cross-validation on the training set. The classification was performed by a linear classifier calculated from Fisher linear discriminant analysis (FDA). The maximum number of features to be selected by SFFS was set to 15.

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After the selection process, the feature set and the corresponding spatial filter which yielded the best fitness value was employed to train the classifier (again FDA) on the whole training set. Classifier, spatial filter and features were then evaluated on the previously unseen test set. Note that no temporal filtering was applied in this evaluation process. Thus, the scheme of the evaluation procedure is similar to Fig. 1B, however, without feature selection.

Results

As mentioned earlier, different ICA implementations were investigated. Additionally, all ICA methods and the CSP method were trained according to scheme A as well as scheme B (c.f. Fig. 2). However, only CSP showed improved performance by using scheme B. To conserve space and achieve a clear and consise representation of the relevant outcome of this investigation, only the results from the algorithms summarized in Table 1 are presented in Table 2 and in Figure 4. These combinations yielded results better than or at least similar to the other combinations we investigated. In any case, results were calculated for the discrimination between AP00 and IDL and between AP05 and IDL.

Table 2: Classification performance.

	no SPF_B		with LAP_B	
	AP00	AP05	AP00	AP05
EEG	0.63±0.08	0.67±0.12	0.65±0.09	0.76±0.11
ECoG	0.70±0.07	0.83±0.10	-	-
	with ICA_B		with CSP_A	
	AP00	AP05	AP00	AP05
EEG	0.72±0.05	0.76±0.10	0.71±0.08	0.81±0.11
ECoG	0.78±0.04	0.90±0.04	0.81±0.06	0.94±0.02

Table 2 shows the classification performance averaged over all subjects with standard deviations for EEG and ECoG data and for all algorithms investigated. The algorithm is denoted by the abbreviation of the spatial filter and a subscript that indicates the scheme used for training. Results of spatial filters derived for the small Laplacian are not displayed, since the topographic distribution of the ECoG channels did not allow the simplified calculation for all datasets investigated. For those ECoG datasets where the topography was appropriate, results were calculated, but they were inferior to those obtained by ICA or CSP.

Figure 4 depicts a graphical representation of the results shown in Table 2. The upper diagram shows the classification performance of discriminating movement-activity (AP05) versus idling. The lower diagram displays the performance for the discrimination task pre-movement activity (AP00) versus idling. The 4 bars on the left hand side represent the classification accuracies obtained from EEG data, the 3 bars on the right hand side show the results found by evaluating ECoG data. Regardless of the recording method, spatially filtered data always produced improved performance rates compared to monopolar data. In general, LAP was inferior to ICA, and ICA was equal or inferior to CSP. Since CSP is the only method that makes explicit use of the class information of each data sample (movement or idling), the superior performance of CSP over the other methods is not surprising. Even more importantly, the application of spatial filters within the suggested signal processing framework to EEG data yielded classification rates similar to those obtained from monopolar ECoG data. On the other hand, the same framework applied to ECoG data resulted in a similar performance gain.

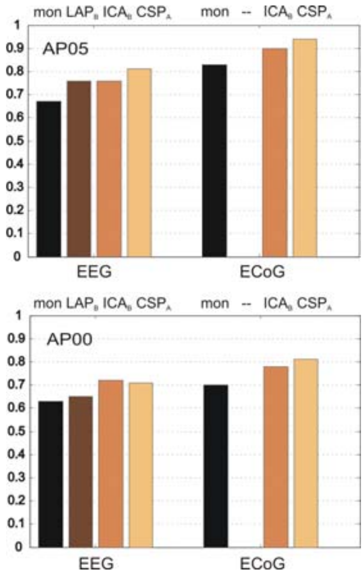

Figure 4: Comparison of classification results for various spatial filters applied to EEG and ECoG data.

Discussion

In this study, we deal with the discrimination between movement and idling. It is important to note that this is a much more difficult problem than discriminating between two spatially distinct tasks such as left and right hand movements. Unlike the movement events that elicite similar brain activity from trial to trial, the idling periods have the potential to be very different from one another thereby complicating their accurate detection. Therefore, our results are expectedly lower than results obtained by discriminating two spatially distinct events. For our comparison, however, it is the relative performance that is important.

The results show that by using a spatial filter which linearly integrates information over multiple spatially distributed sensors, the classification performance in EEG recordings could be significantly increased so that it was almost in the range of the results achieved for unpreprocessed ECoG recordings. However, applying the same preprocessing to ECoG data further improved classification and yielded very high classification rates. In this context it should be noted again that the artifacts

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were removed from our EEG data and that the locations of the ECoG electrodes did not consistently cover brain areas that are known to be most suitable for recording brain patterns associated with motor activity. In a practical BCI, the EEG would be contaminated with artifacts and the ECoG electrodes would be located over sensorimotor areas. Thus, it can be assumed that the differences between EEG and ECoG recordings are even more pronounced in a real BCI than in our investigations. Consequently, the results obtained clearly demonstrate the potential of ECoG as a promising method for direct brain-computer communication.

We also want to emphasize that this was only an attempt at performing a comparison between EEG and ECoG, because for an ideal comparison, EEG and ECoG data recorded simultaneously from the same subjects should be used. However, our clinical setting did not allow such recordings. The ECoG data was solely recorded for the purpose of epilepsy monitoring, which did not include simultaneous EEG recording. In fact, the EEG data was recorded from healthy subjects. That is, EEG and ECoG data were recorded from different subjects. Nevertheless, we think that our results lead to the conclusions stated, since we are comparing the relative increase in performance as a result of applying spatial filters. The point is that we can show that whatever gains are possible when EEG is spatially filtered are also possible when such filters are applied to ECoG. ECoG signals come direct from the cortical surface, whereas EEG is a record of those signals after being distorted and attenuated by skull and tissue. Clearly then, raw ECoG signals are superior to raw EEG signals. The relative improvement achived by applying spatial filters is similar in each case. Therefore, this gives strong evidence to support the view that ECoG remains superior.

Conclusions

Although advanced spatial filtering techniques are able to greatly enhance EEG signals, the results produced only approach the quality of raw ECoG signals. Since these same techniques may equally be applied to ECoG signals, they can be used to improve ECoG signals in the same way. As a result, spatially filtered EEG can not replace ECoG. That is, ECoG signals continue to have the potential to produce better BCI systems than EEG signals.

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