Detection of Event−Related Signals in Electrocorticogram

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Introduction

A direct brain interface (DBI) is defined as a human−computer interface that accepts voluntary commands directly from the brain. The University of Michigan DBI is based on the detection of event related activity in electrocorticogram (ECoG). The movements used here are not prompted by a cue, thus the DBI must detect the execution of a particular movement without the knowledge of when that movement might occur.

Two distinct forms of neural activity have been observed in ECoG during the preparation and execution of a movement. Event−related potentials (ERPs) are time−locked and phase−locked to an externally or internally paced event and can be understood in terms of the response of a stationary system with a specific neuronal circuitry. Event−related desynchronization and synchronization (ERD/ERS) are also time−locked, but not phase−locked, and can be understood as an alteration in the ongoing neural activity resulting from changes in the functional connectivity within the cortex or from changes in various feedback loops [1]. These phenomena may occur individually or linked together spatially and temporally [2].

Methods

The current method for the DBI is based on the single channel detection of ERPs in ECoG [3]. Averaged ECoG templates are developed using triggered averaging, where the trigger is directly derived from some aspect of the external movement. For detection, normalized cross−correlation is performed between the template formed from a training set and the continuous ECoG from the test set, and the result is compared to a set threshold.

This correlation detector is optimal for the model assuming a known signal in additive white Gaussian noise. Experimental observations, however, show that the noise is not white as it is neither uncorrelated nor stationary (see Results). For this model assuming "colored" noise, it can be shown that the optimal detector depends on the covariance of the time samples. The problem with this model is that, because the ERP may last several seconds, we can never expect to have enough event observations from a given subject to estimate the full covariance matrix. Thus, there is no way to implement the optimal detector.

An alternative would be to improve the performance of the detection scheme by using other information present in the ECoG. Neural activity such as ERD/ERS is not phase−locked and, therefore, is absent from the averaged template used in the Gaussian model described above. By using additional features, we can exploit information in the signal that is ignored by the correlation detector. Two feature sets that have been investigated for this purpose are the Hjorth parameters [4] and the adaptive autoregressive parameters [5].

Results

We have identified that both increases and decreases occur in the intertrial variance of the ECoG data that are correlated with the event. This confirms that the noise in the additive Gaussian noise model is not white, and thus the correlation detector is not optimal.

Preliminary results using the additional parameter sets indicate that detection performance may increase on average when certain features are combined with the ERP information. This indicates that additional signal information exists in the ECoG that is not present in the ERP.

Discussion

If we can determine a simplified model for the data by assuming some underlying structure for the covariance of the additive Gaussian noise, then it may be possible to estimate a covariance matrix from the observations that is more descriptive than that assuming white noise. Using this information, an improved detector based on the ERP could then be developed. Future improvements are also expected to result from the identification of the particular features in the data that are most predictive of an event.

References

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