International Congress Series 1300 (2007) 349 – 352

www.ics-elsevier.com

Bayesian classification of index finger movements by analysis of MEG and EEG data

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Abstract. A Bayesian classifier was developed for decoding finger movements by analysis of MEG data. Subjects were monitored by a 151-channel MEG system while making “flicking” motions (up, down, left, right) of the right-hand index finger. The SAM beamformer method was used to spatially localize the brain activity. A classifier was constructed based on signals from 30 to 200 discriminating locations selected from the 1-mm grid. When applied to the test data, 4-way classification rates in the range 50–70% were observed (chance = 25%), with information rates of 0.25–0.7 bits per classification. In several cases simultaneous EEG recordings were made. By calculating regression of SAM signals from discriminating locations on EEG training data, it was possible to accomplish the “informing” of the EEG by MEG. It was shown that even when classification using physical EEG channels failed, informed EEG yielded 40–45% classification rates.

Keywords: MEG; EEG; Brain–machine interface; Single-trial classification

1. Objectives

The main objective of this work was to decode and classify the finger movements by analysis of associated MEG and/or EEG activity. The results may potentially be used in a non-invasive brain-machine interface (BMI, [1]) that would allow an ordinary person to control equipment by thought.

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doi:10.1016/j.ics.2007.03.006

2. Design, materials and methods

2.1. Experimental setup

Four subjects were monitored by a 151-channel whole-cortex MEG system while making four-way body-centered finger "flicking" motions (up, down, left, right: center-out-center flexions–extensions and lateral–medial flexions of the metacarpal–phalangeal joint with a pronate hand). In each experiment, the motion was either self-paced or visually directed. On several occasions simultaneous EEG recording were done using the 10–10 electrode system. Typically, 250–600 movements were made, with random timing and direction. In the self-paced runs the subject's eyes were not fixated. During the visually prompted measurements the eyes were following the target. In all cases the beamformer was focused on the cortical motor areas. Thus, the eye motion artefacts were reliably excluded from the analysis. The direction and onset of finger movement were determined from the magnetic signal of a small finger-mounted coil. The brain fields filtered to the 2- to 32-Hz frequency band were analyzed in a time window 150–370 ms long around the start of the motion markers.

2.2. Bayesian classifier

With MEG data the SAM beamformer method was used to measure brain activity by forming a 1-mm grid of "virtual sensors" in the motor and pre-motor areas of the contra lateral side of the subject's brain and to suppress activity from eye saccades, eye blinks, visual cortex and external interference.

The data were divided into equal-sized "training" and "new" data sets. Then a Bayesian classifier was constructed for decoding the finger movements using the training data only.

In the first stage of the algorithm, a crude selection of discriminating virtual sensors was performed. For each grid voxel v, principal component analysis (PCA) of a time segment $m^{(v,k)}(t)$ around the start of the motion marker established a vector $\boldsymbol{s}^{(v)}(k)$ of (n_v) principal component amplitudes of the kth trial. Typically, n_v=3–15 components were retained for the analysis based on the power threshold. The next step is to group trials according to finger direction classes and perform an ANOVA test for individual PCA amplitudes. The result is n_v ANOVA P-values (P_{ANOVA}) at each grid voxel v. We then select virtual sensors (voxels) that are local minima of P_{ANOVA} with values not exceeding certain threshold α.

Next for each virtual sensor selected in the first stage, a marginal probability of features $\boldsymbol{s}^{(v)}$ conditioned on the class (the motion type) C_i may be calculated assuming that $\boldsymbol{s}^{(v)}$ is a multivariate Gaussian with unknown mean and variance. The result is a multivariate t-distribution $T^{(v)}(\boldsymbol{s}|C_i)$ [2]:

$$T^{(v)}(\boldsymbol{s}|C_i)=\left(\frac{N_i}{\pi(N_i+1)}\right)^{n_v/2}\frac{\Gamma((N_i+1)/2)}{\Gamma((N_i+1-n_v)/2)}|S_i|^{-\frac{1}{2}}\left(1+\frac{N_i(\boldsymbol{s}-\bar{\boldsymbol{s}}_i)^T S_i^{-1}(\boldsymbol{s}-\bar{\boldsymbol{s}}_i)}{N_i+1}\right)^{-\frac{N_i+1}{2}}$$

In this expression, N_i is the number of training trials for C_i, and $\bar{\boldsymbol{s}}_i$,S_i are the mean and the scatter matrix of features calculated on the training subset for class C_i:

$$\bar{\boldsymbol{s}}_i=(1/N_i)\sum\nolimits_{k\in C_i}\boldsymbol{s}(k);\qquad S_i=\sum\nolimits_{k\in C_i}(\boldsymbol{s}(k)-\bar{\boldsymbol{s}}_i)(\boldsymbol{s}(k)-\bar{\boldsymbol{s}}_i)^T.$$