To extract the Independent Components of the evoked potentials in the EEG using ICA

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INTRODUCTION

The aim was to develop a reliable method of extracting the independent components of single trial evoked potential (EP) signals to derive features for the subject's bioprofile, for diagnostic, prognostic, and monitoring purposes. Single trials are of interest, because conventional averaging conceals trial-to-trial variability and hence information. Independent Components Analysis (ICA) is a technique for Blind Source Separation (BSS) to recover N temporally independent source signals $\mathbf{s} = \{s_1(t), \dots, s_N(t)\}$ from N linear mixtures (the observations), $\mathbf{x} = \{x_1(t), \dots, x_N(t)\}$ obtained by multiplying the matrix of unknown sources s by an unknown mixing matrix A, (x = A.s). ICA seeks a square unmixing matrix W such that s = W.x. Difficulties arise for short duration, relatively low amplitude EPs, which have sparse ICs. The effectiveness of different algorithms was compared. Problems associated with more sources than measurement electrodes and with the generation by the algorithms of artefactual components were investigated. Ways of extracting the true EP components were considered. Component grouping was

applied to obtain reliable groups, which could be explored for any clinical interpretations. Here we describe the recommended approach as developed by our virtual research group.

Material and methods

After applying ICA (imax) [1], the ICs are grouped based on their, peaks, latencies and the columns of the corresponding mixing matrices. Different methods of clustering were investigated, leading to the choice of the unsupervised k-means clustering approach for determining the possible number of clusters.

The method was tested using two simulated data sets with various scenarios: (1) synthetic data sets with uniformly distributed added noise and fixed source-latencies (2) synthetic data sets with EEG-like added noise and fixed source-latencies [2]. This was repeated using time-varying latencies.

We subsequently studied the following data sets: (1) 64 CNV (Contingent Negative Variation) trials obtained from one subject (2) 520 P300 trials from 9 normal subjects and (3) 200 P300 trials from 4 Alzheimer's disease subjects.

RESULTS AND DISCUSSION

An analysis procedure has been developed for extracting the ICs of single trial EPs from single trial recordings. Analysis of CNV and P300 recordings yielded some components,

which corresponded to earlier findings, but also some additional components. Differences were found in the ICs of the P300 between normal and Alzheimer's disease subjects. Inter-trial variability in temporally coinciding positive and negative ICs may explain the observed variability in the peaks observed in averaged P300s.

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