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# What (Not Where) are the Sources of the EEG?

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#### Introduction

The problem of determining brain electrical sources from potential patterns recorded on the scalp surface is mathematically underdetermined. Most efforts to identify EEG sources have focused on performing simultaneous spatial segregation and localization of source activity. Recently, we have applied the ICA algorithm of Bell and Sejnowski [1] to the problem of EEG source identification (What?) considered apart from source localization (Where?) [2]. By maximizing the joint entropy of a set of output channels derived from input signals by linear filtering without time delays, the ICA algorithm attempts to derive independent source waveforms from highly correlated scalp EEG signals without regard to the physical locations or configurations (focal or diffuse) of the source generators.

In our simulations, we used a prewhitening technique described in [3] and a 'natural gradient' feature introduced in [4] to speed network training. The ICA algorithm performs near ideal source separation when,

- (1) the actual sources are independent,
- (2) the propagation delays of the mixing medium (here, brain volume conduction) are negligible,
- (3) the sources have central probability density functions not too unlike the derivative of the logistic sigmoid, and
- (4) the number of independent signal sources is the same as the number of sensors.

Here, we report simulation experiments to determine (1) whether the ICA algorithm can successfully isolate independent components in simulated EEG generated by focal and distributed sources, and (2) whether ICA performance is severely affected by sensor noise and additional low-level brain noise sources.

#### Methods

A three-shell spherical head model developed by Anders Dale and Martin Sereno [5] was used to test the ability of ICA to separate known signal waveforms projected to six simulated scalp electrodes from five simulated brain source dipole locations. Six nine-second audio signals (man's voice, woman's voice, gong, chorus, synthesizer, drum) were recorded, scaled to different levels, assigned to one or two brain dipoles, and mathematically projected to the six simulated scalp electrodes to produce

simulated EEG signals. In some conditions, six additional simulated brain noise sources were introduced (at nearby diffuse-dipole locations) by projecting Gaussian white noise through the scaled and slightly perturbed source signal mixing matrix, and low-level simulated EEG sensor noise, consisting of independent Gaussian white noise, was added to each simulated EEG channel.

#### Results

Results of the simulations showed: (a) ICA transforms of simulated EEG signals are insensitive to initial weights, (b) In the no-noise condition, ICA separated all six simulated EEG signals with a signal-to-noise ratio (SNR) above 30 dB, (c) In the presence of brain and sensor noise sources, ICA performance degraded smoothly as noise levels were increased relative to those of the sources of interest. Thus, ICA should segregate relatively strong, independent EEG sources into separate output channels with satisfactory SNR. We will show examples of ICA applied to actual EEG and cognitive ERP data [6].

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