Independent Component Analysis of EEG recorded during two-person game playing

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September 5, 2007

Abstract

We report a study on two-person game playing involving simultaneous EEG recording from both subjects. Independent Component Analysis is used for identifying activities of individual cortical EEG sources. Activity of a midline fronto-central component is identified in four of five subjects. This component accounts for the P300 waveform whose amplitude varies depending on the success in the gaming situation.

1 Introduction

This report is about first results in a neuroscientific study of two-person game playing. A number of recent studies on game playing monkeys using implanted electrodes have produced new insights into the function of the brain. These types of studies have successfully linked single cell firing rates to mathematical behavioural models, thereby producing a new field of research sometimes termed neuroeconomics (see [Glimcher 2003] for a comprehensive introduction). Our experiment seeks to clarify whether a similar study can find evaluative signals in scalp EEG signals recorded non-invasively from humans.

In our EEG experiment two subjects are tested at once, competing against one another in a simple "Same/Different" game formally akin to the classical game of "Matching Pennies" (see e.g. [Camerer 2004]). We use Independent Component Analysis (ICA) (see [Comon 1994], [Bell & Sejnowski 1995] and [Makeig et al. 1996]) to decompose EEG recorded during the game into non-brain artifacts and spontaneous EEG activity. During the games, the largest non-artifact component in all but one subject had a midline fronto-central localisation and gave rise to a late positive component after auditory feedback. This component accounts for a portion of the well known P300 waveform [Sutton et al. 1965]. We show that the amplitude of this EEG component is larger for losses than for wins in the game.

2 Methods

2.1 Game

The recording of the human electro encephalogram (EEG) is a non-invasive method of recording electric brain potentials from the human scalp via a set of electrodes. In our EEG experiment two subjects were tested at once, competing against one another in a simple "Same/Different" game. During these experiments, each subject wore 128 EEG electrodes positioned evenly across the head, plus four sub-ocular electrodes recording their eye movements (EOG). Simultaneous recording of their EEG and EOG was acquired using a custom two-subject Biosemi EEG system. We recorded data from three pairs of subjects (male, right handed, age $= 29.6 \pm 9.29$ sd) who did not know each other prior to the experiment. Data were recorded with a sampling rate of 256 Hz, FIR-filtered with a bandpass from 1 to $50Hz$ and then down-sampled to $128Hz$.

Both subjects were seated facing one another in the experiment room. Subjects were asked to avoid communicating to each other during the experimental session, including during breaks. Between the subjects, two LCD screens, placed below face level, were used to deliver visual feedback. Each subject held a response button in their dominant hand. The two LCD screens shielded each participant's view of the other participant's hand and button, without blocking the view of the other subject's face. Subjects were instructed to look at their competitor's face when actually playing. Each subject wore ear insert headphones that delivered individual performance feedback during the game.

Participants competed against one another in a simple "Same/Different" game formally akin to the classical game of "Matching Pennies". Matching Pennies is a zero-sum game with two players (see e.g. [Camerer 2004]). In each play, each player shows one side of a coin, either heads or tails, to the other. If both players' coins show heads or both tails, then player One wins, otherwise player Two wins. Matching Pennies is one in a family of games in which one person benefits from a "match" whereas the other benefits from a "mismatch". Rational human beings, when confronted with this strategic conflict reach a behavioural equilibrium at which the average subjective desirability of the two actions comes to equivalence (see e.g. [Nash 1950]).

Participants were first taught the game including a short practice period. They were told whether they had been assigned to play the "Same" or the

"Different"strategy. During the game, the "Same" player was rewarded with points and positive auditory feedback for having the response button in the same position as that of their competitor (up = up or down = down). The "Different" player was rewarded for having it in the different position from that of their competitor (up $\neq$ down or down $\neq$ up). At the end of the game playing session a bonus of \$25 was divided between both players according to the ratio of points earned during the game. If one of the players ended the game with zero points or a negative score, the other one received the whole bonus. Any bonus was in addition to the standard hourly rate. The pseudo-code like representation in Tab. 1, plus the next paragraphs more formally describe the game.

The game session consisted of four `BLOCK`s of ten `BOUT`s. Each `BOUT` consisted of twenty `PLAY`s. Each `BOUT` started with the instruction "READY" displayed on both LCD screens for two seconds (`display(READY,2sec)`). This was followed automatically by the display of the instruction "PLAY" (`display(PLAY,until BOUT end)`) which stayed on the screens for the rest of the `BOUT`.

Players then covertly pressed and released their response button at self-chosen intervals to maximise the chance of holding it either in the same or different position than the other player. At irregular, 1-5 sec intervals chosen at random by the computer running the game (`wait(1-5sec)`), the computer tallied the relative position of the two participants' buttons, computed points won or lost by each subject, and rewarded one participant with positive auditory feedback ("beep"[1]) and the other with concurrent negative feedback ("buzz"[2]) (`evaluate-and-feedback`).

To minimize rapid button pressing by either subject, points awarded for each winning `PLAY`, and lost for each losing `PLAY`, were proportional to the length of time the subject had held the button in the same position (to a maximum of 5 sec). To minimize the chance of any participant ending the session with a negative point total, points lost in a `PLAY` increased with hold time at a slower rate than points won. Larger point gains are indicated to subjects with higher-pitched ("beep") feedback; larger point losses were indicated by lower-pitched ("buzz") feedback[3].

After twenty `PLAY`s, the `BOUT` was completed. The two LCD screens

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[1]Sinus wave, .2 sec duration, 1300 Hz frequency, 10% on- and off-ramp.

[2]Sawtooth wave, .2 sec duration, 500 Hz frequency, 10% on- and off-ramp.

[3]Adding or subtracting 50 or 100 Hz to the basic "beep" or "buzz" sounds.

indicated the total number of points won/lost during the last `BOUT` (`display(RESULT-BOUT,until button presses)`), and then the scoring in the session so far (`display(RESULT-TOTAL,until button presses)`). The last display also showed each of the players the share of the bonus (in US dollars) they would earn if the game ended right then. The next `BOUT` began after both players pressed their response button at least once.

After twenty `BOUT` periods a game `BLOCK` was completed. Between `BLOCK`s, subjects were allowed to relax (`if not (BLOCK == 4)`) by stretching, closing their eyes, etc. Players were allowed to talk to the instructor but not to each other. This was indicated by displaying the instruction "RELAX" on the LCD screens (`display(RELAX,until instructor restart)`). The game resumed after both players told the instructor they were ready to begin again. After four game `BLOCK`s, the LCD screen displayed final scores and shares of the bonus to both players (`display(RESULT-FINAL)`).

One complete "Same/Different" session required about $4 \times 10 \times 20$ `PLAY`s $\times 3sec = 40min$ not including break times between blocks and bouts. Therefore the game session lasted less than an hour.

2.2 Preprocessing

Before any further processing of the data, channels which were noisy for the majority of the recording period (e.g. due to drift or bad contact) and segments containing severe artifacts (disturbances across many channels) were deleted. One subject had to be excluded from further analysis because of problems with the ear insert headphones during the game. This left five subjects for the analysis.

2.3 Analysis

Rather then analysing the raw EEG we used Independent Component Analysis (ICA) to decompose the EEG recorded during the game into artifacts and spontaneous EEG activity. This allows us to get a clearer and more artifact-free picture of the activities of individual cortical sources [Makeig et al. 2004].

Independent Component Analysis (ICA) [Comon 1994] is one of a group of algorithms that attempt to achieve blind separation of sources [Jutten & Herault 1991]. To estimate the original sources from an observed mixture, while knowing little about the mixing process and making only

few assumptions about it and about the sources, is called blind separation of sources. ICA allows recovery of N independent source signals $s = \{s_1(t), s_2(t), \ldots, s_N(t)\}$ from N linear mixtures, $x = \{x_1(t), x_2(t), \ldots, x_N(t)\}$, modelled as the result of multiplying the matrix of source activity waveforms, s, by an unknown square matrix A (i.e. $x = As$). The task is to recover a version, u, of the original sources s, save for scaling and ordering. To this purpose, it is necessary to find a square matrix W specifying filters that linearly invert the mixing process (i.e. $u = Wx$).

By the central limit theorem a linear mixture of independent random variables is necessarily more Gaussian than the original variables. Therefore maximizing the nongaussianity achieves the unmixing of the recorded signals x. This implies (i) that it is sufficient to assume that the source signals $s(t)$ are *statistically independent* at each time step t, though their mixtures $x(t)$ are not; (ii) that in ICA we must restrict ourselves to at most one Gaussian source signal. Since there exist numerous ways to measure nongaussianity (e.g. kurtosis, negentropy, etc.) and different approaches towards information maximization, ICA researchers have developed a family of algorithms for solving the blind source separation problem (see e.g. [Lee 1998], [Hyvaerinen 1999b] and [Roberts & Everson 2001] for an introduction and overview).

Applied to simulated data sets for which the ICA assumptions are fulfilled, leading ICA algorithms (including "infomax" [Bell & Sejnowski 1995], "JADE" [Cardoso & Souloumiac 1993] and "FastICA" [Hyvaerinen 1999a]) return near equivalent independent components (see [Delorme & Makeig 2004] for a discussion of differences between ICA algorithms). However, the physiological significance of any differences in the results of the same or different algorithms has not yet been systematically tested. Differences in ICA decompositions have been reported for neural ensemble data [Laubach et al. 1999] and fMRI data (see [Duann et al. 2001] and [Esposito et al. 2002]). To confront these difficulties we adopt the following approach: (i) use an ICA algorithm which has been shown to be well suited for decomposition of EEG data ("infomax"), (ii) analyze only dominant independent components which account for a large portion of the variance in the data and which are therefore known to be more stable than smaller ones.

We used the "infomax" neural network algorithm [Bell & Sejnowski 1995]

for ICA as implemented by [Makeig et al. 1997][4]. This approach uses the fact that maximising the joint entropy, $H(y)$, of the output of a neural processor minimises the mutual information among the output components, $y_I = g(u_i)$, where $g(u_i)$ is an inverted bounded nonlinearity and $u = Wx$.

The "infomax" algorithm has repeatedly been shown to reliably find independent components that are physiologically plausible, functionally distinct, and often have spatial and functional similarities across data sets, sessions and subjects (see e.g. [Delorme et al. 2002] and [Makeig et al. 2002]). Many of the biologically plausible sources "infomax" identifies in EEG have scalp maps closely fitting the projection of a single equivalent current dipole (see again [Makeig et al. 2002] and [Jung et al. 2001]).

When using ICA for EEG analysis (see e.g. [Vigario 1997], [Jung et al. 2001] and [Makeig et al. 2002]), the rows of the input matrix x are EEG signals (and possibly EOG or other signals relevant for the experiment) recorded at different electrodes and the columns are measurements at different time points. ICA finds an unmixing matrix W which linearly decomposes the multichannel data into a sum of maximally temporally independent and spatially fixed components $u = Wx$. The rows of the output matrix u are courses of activation of the independent components (ICs). These components account for artifacts, stimulus and response locked events and spontaneous EEG activity. The columns of the inverse matrix W^{-1} give the relative projection strengths of the respective ICs at each of the scalp sensors. These scalp maps of projection strengths provide evidence for the components' physiological origin (e.g. ocular activity projects mainly to frontal sites). Selected components can be projected back onto the scalp using the relation $x_0 = W^{-1}u_0$, where u_0 is the matrix u with irrelevant components set to zero. Thereby brain signals accounted for by the selected components can be obtained in their true polarity and amplitudes.

3   Results

We computed infomax ICA for each of the five subjects separately. The respective input matrices x consisted of all EEG and EOG channels from one subject remaining after manual artifact inspection (see end of Sec. 2.1). We

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[4]All ICA related computations were done with the MATLAB toolbox EEGLAB [Delorme & Makeig 2004].

used principal component analysis to reduce the dimensionality of the input channels to 90. We found this to be advantageous for numerical reasons. ICA outputs the IC activations u and the square matrix W specifying the filters that invert the mixing process ($u = Wx$). We inspected topographical plots of all IC scalp maps (the columns of the inverse matrix W^{-1}) for all subjects after sorting the components in descending order of their mean projected variance (using $x_0 = W^{-1}u_0$). We chose independent components for further analysis based on the following considerations:

- take only components which account for a large portion of the variance to guarantee reproducibility of results

- take only components which are stable across subjects, i.e. which show similar characteristics (comparable IC scalp maps and power spectra of IC activations) in all or most subjects

From this it should be evident that we tried to be quite conservative in choosing independent components. This is especially important given the rather small number of subjects in our study.

For four of the five subjects, we found a component with midline fronto-central localisation to be a principal non-artifact component (artifact components account for eye movements, muscle noise etc.). For three subjects this component was the largest non-artifact component, for one the second largest. Topographical plots of these four components are depicted in Fig. 1. Since ICA estimates u and W only up to an arbitrary scaling factor, topographical plots are made after transformation to z-scores to allow for comparability across subjects.

In a next step we epoched the IC activations u of each of the four subjects around the auditory feedback events. At the end of each `PLAY` there was an `evaluate-and-feedback`-event consisting of an auditory feedback in the form of a "beep" (positive for a win) or a "buzz" (negative for a loss). Within each experiment there were 800 such stimuli, the number being decreased by artifact rejection later on. A "feedback-locked epoch" consisted of the activation of an IC one second prior to two seconds after the feedback stimuli. Average activations for the four ICs shown in Fig. 1 time-locked to the feedback event are given in Fig. 2. Since ICA estimates the IC activations u only up to an arbitrary scaling factor, we normalised the average activations to allow for comparison across subjects (z-score transformation to zero mean and unit standard deviation).

The most prominent feature of all four averages seems to be a positive going waveform starting about 300 ms after stimulus onset. We estimated the peak of this activity by finding the maximum of each average between 300 and 400 ms after stimulus onset. The second vertical line in each plot indicates this maximum. The average latency of these peaks is 339.8 $ms \pm 37.5$ sd after stimulus onset. This positive going waveform accounted for a portion of the well known P300 waveform (see e.g. [Sutton et al. 1965]).

Each of the feedback events is equivalent to a win or a loss for the subjects. Our goal was to find a relation between the context of wins and losses and the IC activations. For each of the four subjects we computed averages across the activations in single trials of their respective fronto-central components separately for wins and losses (W and L). For each of the averages we computed an estimate of P300 amplitude, $P300amp$, by taking the mean of the average IC activation from 50 ms before to 50 ms after its peak (see above for how the peak was found). We subtracted the mean of a one second pre-stimulus baseline from this P300 amplitude estimate. We expressed the differences of the W and L averages as percentages by computing a $P300amp$ estimate from the average across all feedback epochs from a subject (no matter whether it was win or loss, see Fig. 2), setting this to be 100% and expressing all other $P300amp$ as percentages relative to this overall estimate. These $P300amp$ estimates expressed in percentages are given in Tab. 2 separately for wins and losses for all four subjects. The $P300amp$ for losses is bigger than the one for wins for all four subjects.

The average $P300amp$ estimate across subjects for wins is 88.82 ± 7.17 versus 111.78 ± 8.12 for losses. The corresponding t-value (paired t-test) is $|t| = |-3.0047|$ which gives a probability of $p = .057$ under the null hypothesis of no differences between wins and losses. Using a conventional error level of $\alpha = .05$ the difference between the $P300amp$ estimate for wins and losses is just not significant. The main reason for this seems to be the very small number of only four subjects. With just one more subject and hence one more degree of freedom for the t-test the above result would indeed have turned out significant.

4   Discussion

The P300 waveform is one of the most widely studied endogenous evoked potentials (see e.g. [Sutton et al. 1965], [Altenmueller & Gerloff 1999] for a

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standard text book treatment, [Soltani & Knight 2001] for a recent review). As an endogenous evoked potential, it should be relatively immune to the influence of stimulus parameters. There is some evidence that auditory stimulus intensity increases P300 amplitude and that lower frequency marginally affect stimulus latency [Sugg & Polich 1995]. The auditory feedback in our experiment ("beep" and "buzz") was presented with matching intensity and we did not analyse latency of P300 components anyway. Therefore, differences between "win" and "loss" situations found in the EEG can be attributed to higher cognitive functions.

The most common paradigm for eliciting a P300 is to randomly intersperse infrequent and therefore unexpected stimuli among frequent stimuli presented to an attentive subject. This is known as the "oddball paradigm". The amplitude of the P300 is inversely related to the stimulus probability. P300 amplitude is also modulated by subjective outcome probability in an inverse relationship. The latency of the P300 seems to be related to task difficulty [Polich 1992]. The "oddball paradigm" has been used to study a wide variety of information processing issues (see [Polich & Kok 1995] for an integrative review of cognitive and biological determinants of P300). For our experiment, on average, subjects win and lose equally often during a full game session as expected from game theory. This is called Nash-equilibrium where a behavioural equilibrium is reached at which the average subjective desirability of the two actions in the game comes to equivalence (see e.g. [Nash 1950]). Therefore the auditory feedbacks in our experiment are equally probable on average and cannot be analysed in an "oddball paradigm" framework.

Although the theoretical meaning of the P300 is not yet completely clear, the majority of data are consistent with some form of context updating and information processing. Our work is not intended to add to the ongoing discussions on the meaning of P300 but rather to present proof that it is possible in principal to link parameters derived from average evoked potentials to the context of the gaming situation in our experiment. It seems to be the case that the negative feedback following a loss acts as an averse stimuli giving rise to a larger P300 amplitude similar to the averse nature of an unexpected stimuli in the conventional "oddball paradigm".

There are only few neuroscientific studies of social interaction engaging human subjects in game playing. Most closely related to our approach is probably an fMRI study using the children's game "Paper/Rock/Scissors" [Paulus et al. 2004] which is formally akin to a game of matching pennies with three sided coins. The authors use a temporal difference model to ex-

plain their subjects' behavior when playing against a computer. Over the course of the experiment they changed the prior probabilities of the computer playing "Rock", "Paper" or "Scissors". The main result was that a trend process derived from the temporal difference model accurately tracked these changes in prior probabilities and was time-locked to the hemodynamic changes in the inferior frontal gyrus. Contrary to this study, the prior probabilities for our "Same/Different" game were not systematically changed. They rather evolved around the theoretical equilibria due to the subjects' behavior. [McCabe et al. 2001] had their subjects play a "Trust"-game while recording their fMRI. Their study focused on differences between trials in which subjects played against humans versus trials in which they played against a computer. [Rilling et al. 2002] report differences between cooperative and non-cooperative phases during games of the so-called "Prisoner's Dilemma", monitored using fMRI with only one player being scanned. [Fukui et al. 2005] present a study on decision making under uncertainty using fMRI to observe subjects during a card game against a computer. Activity of the medial prefrontal cortex is found to best differentiate between risky and safe conditions.

There are even fewer studies that try to simultaneously monitor brain function of two subjects engaged in any form of social interaction. [Montague et al. 2002] performed simultaneous fMRI in different scanners with pairs of individuals competing against each other in a simple game. The usage of different scanners in different locations has been termed "hyperscanning". The game was designed to measure the effect of deception in a competitive context. Their study is rather a proof of principle experiment than a thorough, neuroscientific study of game playing in humans. [King-Casas et al. 2005] use the same hyperscanning approach for studying neural correlates of the expression and repayment of trust between interacting anonymous human subjects.

To our knowledge, no one has yet looked into human game playing using simultaneous EEG measurements. In our study of two-person game playing, we have successfully linked the context of the gaming situation to parameters derived from average evoked potentials. This can be seen as a first step toward extending results obtained for single cell firing rates of primates and fMRI measurements of humans to EEG in humans. Average evoked potentials in different game contexts account only for a small part of the event-related brain dynamics one could study. [Makeig et al. 2004] give a systematic view of how to use ICA to go beyond simple response averaging.

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Given that the midline fronto-central independent components we described are the largest non-artifact components, they nevertheless seemed to be an important part of the overall story.

5 Conclusion

We presented a first pilot study on human game playing using simultaneous EEG measurements. We were able to successfully link the context of the gaming situation (wins and losses) to parameters derived from average evoked potentials (P300 amplitude). Given the small number of subjects in our study as well as the fact that we only started to account for the full dynamics of event-related brain dynamics, this should be seen only as a small first step towards the applicability of EEG measurements in the field of neuroeconomics.

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Table 1: Outline of "Same/Different" game.

```
for BLOCK = 1 : 4
   for BOUT = 1 : 10
      display(READY,2sec)
      display(PLAY,until BOUT end)
      for PLAY = 1 : 20
         wait(1-5sec)
         evaluate_and_feedback
      end
      display(RESULT-BOUT,until button presses)
      display(RESULT-TOTAL,until button presses)
   end
   if not (BLOCK == 4)
      display(RELAX,until instructor restart)
   end
end
display(RESULT-FINAL)
```

Table 2: $P300amp$ estimates expressed in percentages separately for wins and losses for all four subjects.

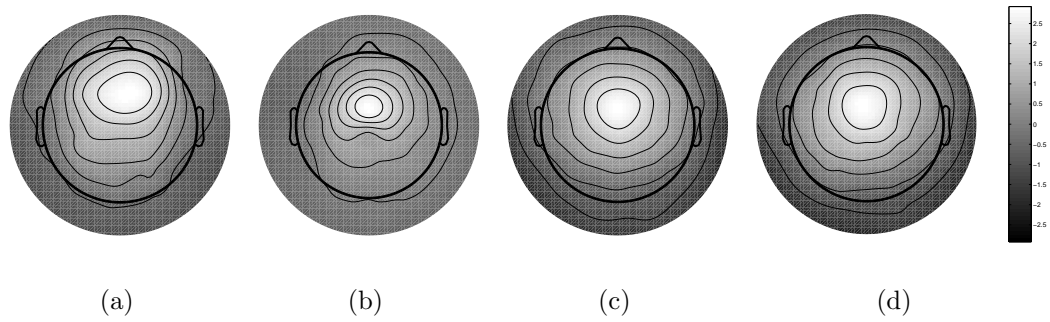| % P300amp	subject 1	subject 2	subject 3	subject 4
win	81.76	83.54	94.78	95.21
loss	119.44	118.15	104.68	104.85

Figure 1: Topographical plots of largest non-artifact independent components for subject1 (a), subject2 (b), subject3 (c), subject4 (d). Given in z-scores, white being positive and black negative.
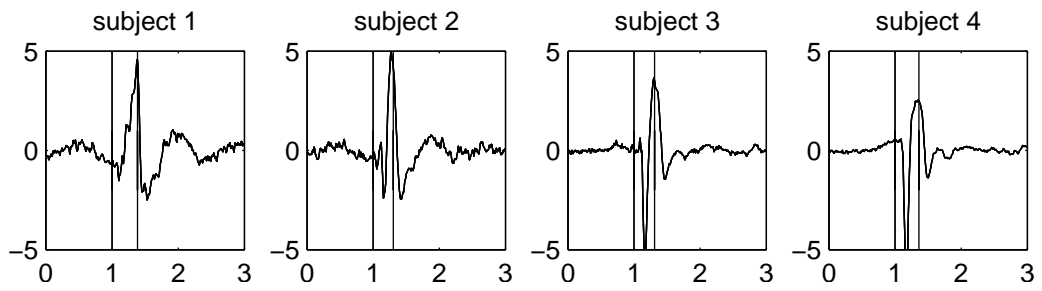
Figure 2: Average normalized IC activations, x-axis are seconds, y-axis amplitude of activations, first vertical line in each plot is stimulus onset, second is estimated peak of P300 activity.