# EEG Data of Face Recognition in Case of Biological Compatible Changes: A Pilot Study on Healthy People

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Keywords:     Face Recognition, EEG Data, Power Spectral Density.

Abstract:     Recognizing people from their faces has a strong impact on social interaction. In this paper we present a pilot study on healthy people where brain activities during a face recognition task have been recorded using electroencephalogram (EEG). Target images (previously seen in a training phase), were presented in the recognition phase in two different conditions: identical to those of the initial phase, modified with biologically plausible changes (such as features enlargement or changed expression) and randomly presented with new faces. The raw EEG data were properly cleaned from both biological or non-physiological artifacts. Statistically significant differences in brain activations were registered between the two experimental conditions, especially in the frontal area, during the recognition process. The results of the analysis on this database of healthy people can be useful as baseline for further studies on people affected by congenital prosopagnosia or autism.

## 1 INTRODUCTION

Being able to study brain responses to a specific set of stimuli represents a way to access new knowledge on how the cognitive processes are activated in a task-based environment and if there are discriminations between subjects affected or unaffected by cognitive impairments.

The electroencephalogram (EEG) is considered a useful mean to obtain the aforementioned information. The EEG is in fact a multi-channel signal, which measures cerebral bio-electric potentials using electrodes positioned on the scalp and thus the brain activities and functions with temporal resolution (Dickter and Kieffaber, 2013). In this work we collected EEG multi-channel data, recorded during a face recognition task. The study of face recognition has been intense in the last decades not only in cognitive researches, but also in computer vision and surveillance applications (Zhao et al., 2003; Cevikalp and Triggs, 2010).

Recognizing people from their faces has a strong impact on social interaction, e.g. to discriminate a friend from a foe, to precisely identify an individual and try to understand his/her behavior or mood, or to be able to interpret an emotive state starting from facial gestures.

The human brain of healthy people is generally able to recognize a specific face, even if its characteristics have changed for various reasons, as getting older or the simple use of make-up. Several face recognition researches used as stimuli, i.e. faces to be recognized, images of well known personalities (e.g. politicians, athletes, actors). The task was generally to discriminate between familiar and unfamiliar faces (Sun et al., 2012; Li et al., 2015; Özbeyaz and Arıca, 2018). This study was designed in order to trace the brain activity linked to different mechanisms involved in face recognition. In particular, we recorded the EEG signal on a healthy population by using a double task that consisted of: recognizing a face as previously presented or new and indicating whether the already seen face was identical or modified. The modified faces had biological compatible changes of features (e.g. eye magnified, mouth reduced) or facial expression (e.g. happiness, sadness). The paradigm was the same used in previous behavioral studies (Daini et al., 2014; Malaspina et al., 2014) for investigating face recognition in individuals affected by congenital prosopagnosia (i.e. a developmental impairment of the ability of recognizing people from their face) or autism. Our aim was to create a pilot scheme on normal recognizers of brain activities analyzed through EEG data to be

used with atypical development populations to verify the involvement of hypothesized psychophysiological mechanisms. EEG data are easily affected by noise (artifacts), which may be caused by peculiar biological or non-physiological conditions and thus should be processed to obtain a cleaner signal without loss of useful experimental data. Instead of rejecting track portions presenting noise, numerous studies have suggested different artifact removal approaches: band-pass filtering trials (Itier and Taylor, 2004), using on-line filters (Parketny et al., 2015), applying a combination of high-pass and low-pass Butterworth filters and rejecting manually only the ocular artifacts (i.e. eye blinking or horizontal eye movements) (Caharel et al., 2015). Other studies have defined multiple steps that combine the techniques previously listed and thus applied low-pass filtering, down-sampling, band-pass filtering, manual pruning and adding the Independent Component Analysis (ICA) for ocular artifacts rejection and baseline corrections over subject epochs (Barragan-Jason et al., 2015).

In this work we present a pipeline for artifact suppression, that does not stretch too much the actual electrophysiological signal. Finally, on the cleared data the Power Spectral Density (PSD) was estimated for each channel and frequency rhythm (alpha, beta and gamma) through the Welch's method. Thus the main contributions of this work are:

- A database of raw EEG data, acquired on 17 healthy subjects during a face recognition task, as described in Section 2.

- A semiautomatic procedure to clean the raw data, and the clean EEG data obtained (see Section 3).

- A statistically significant evidence that there are differences in brain activations especially in the frontal area during the recognition process that makes this database suitable to be a pilot study for further analysis on people affected by congenital prosopagnosia or autism (see Section 4).

## 2 EXPERIMENTAL SETUP

### 2.1 Subjects

The experiment was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki and fulfilled the ethical standard procedure recommended by the Italian Association of Psychology (AIP). The experimental protocols were approved by the ethical committee of the University of Milano-Bicocca. All the participants were volunteers and gave their informed consent to the study. Twenty subjects (eleven females), aged between 18 and 30 (mean = 24.6; SD = 1.7), participated in the experiment. All of them declared no neurological or neuropsychological deficits and had normal or corrected to normal vision.

### 2.2 Stimuli and Tasks

Stimuli were selected from a database previously used in (Daini et al., 2014) and generated by (Comparetti et al., 2011). The neutral faces were created from digital photos of real faces by means of Adobe Photoshop and Poser 5.0 software (Curios Lab, Inc., ad e-frontier, Inc., Santa Cruz, CA). Starting from these neutral faces, (Comparetti et al., 2011) made different kinds of manipulations, modifying features or facial expressions. For more details about how the faces were created please refer to (Daini et al., 2014).

In Figure 1 the two neutral faces used as target stimuli and some of their modified versions are shown.

The experiment consisted of four main phases:

- An adaptation phase, where ten iterations of the two target stimuli (neutral faces corresponding to two identities) were presented to each participant.

- A trial phase, where a set of 20 random faces were presented. This set consisted of the two target neutral faces together with the modified versions (for a total of eight stimuli) and twelve distractors (non-target faces and some of their modified versions). Before the stimulus presentation, a fixation point was displayed on the screen for 500 ms. The stimulus appeared for 500 ms. The subject had to answer (with a mouse click) if she/he recognized the identity shown in the stimulus (identity task). In case of affirmative response, the subject had also to answer if the target was exactly the same previously seen in the adaptation phase, i.e. without any facial modification (neutral task). The type of modification was not asked. The subjects had also to discriminate the non-target stimuli, answering negatively to the identity task (table 1).

- Two experimental phases each consisting of 320 stimuli, with the same scheme presentation as the trial phase. These stimuli were randomly chosen from 640 ones composed of 320 repetitions of the two target faces and all their modified versions and 320 distractors (non-target faces and their modifications). The answers to the identity and neutral tasks were collected and successively used to label the events. Each answer time limit
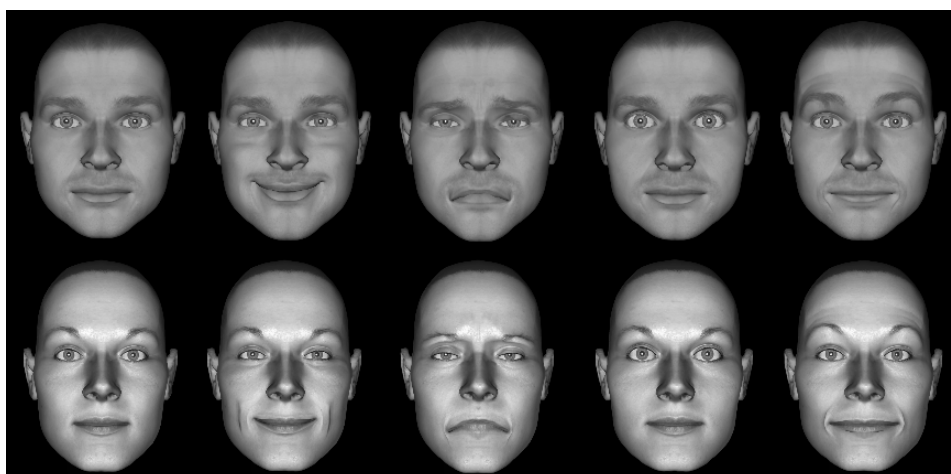
Figure 1: Two neutral basic stimuli (first column) together with some of their modified versions.

Table 1: Case scenarios. The identity task corresponds to the question: 'Is the face a target one?'. The neutral task appears only if the answer to the identity one is affirmative: 'Is the target identical to the one seen in the adaptation phase (subsection 2.3)?'. In case of non-target face, the correct answer to the task question is 'no' and the neutral task question does not appear.

| Stimulus | State | Identity task | Neutral task |
|---|---|---|---|
| | neutral basic target | yes | yes |
| | modified target | yes | no |
| | non-target | no | not asked |

was set to 2000ms. After that time a new iteration is performed, and the one with a missed answer is considered as a wrong answer.

The stimuli presentation (Figure 2) was developed with OpenSesame and triggers sent to the recording computer to keep track of the event time.

In this work we have considered the following four possible events:

- Correct IDentification of the neutral basic Target (CIDT), i.e. one of the faces displayed in the adaptation phase (see section 2.3);

- Correct perception of the MODified Target (CMODT);

- Correct answer over a Non-target stimulus Recognition (CNR), i.e. a face that was not displayed in the adaptation phase;

- ERRoneous response (ERR).

Each trigger was labeled accordingly to the answer types, identifying the four events CIDT, CMODT, CNR and ERR.

From the analysis of the answers, three subjects were excluded from the study due to technical faults and accuracy lesser than 50% in the recognition tasks. The EEG signals of the remaining seventeen subjects were preprocessed and analyzed.

## 2.3 EEG Data Recording

Each subject was prepared for the recording and had to wear the appropriate EEG cap, a Brain Products GmbH EasyCap, following the standard 10-20 system to which were added the AFz, PO9, PO10, Oz electrodes. The electrodes positions are reported in Figure 3. Four sensors were placed under and beside the right eye for ocular artifacts tracking and on the earlobes as ground and reference channels.

Afterward the subject was asked to sit in front of a monitor in a soundproof Faraday cage and exposed to the experiment.

## 3 DATA PREPROCESSING

All the procedures for noise removal were developed using MATLAB, and EEGLAB (Delorme and Makeig, 2004) (MATLAB tool for EEG signal processing and analysis).
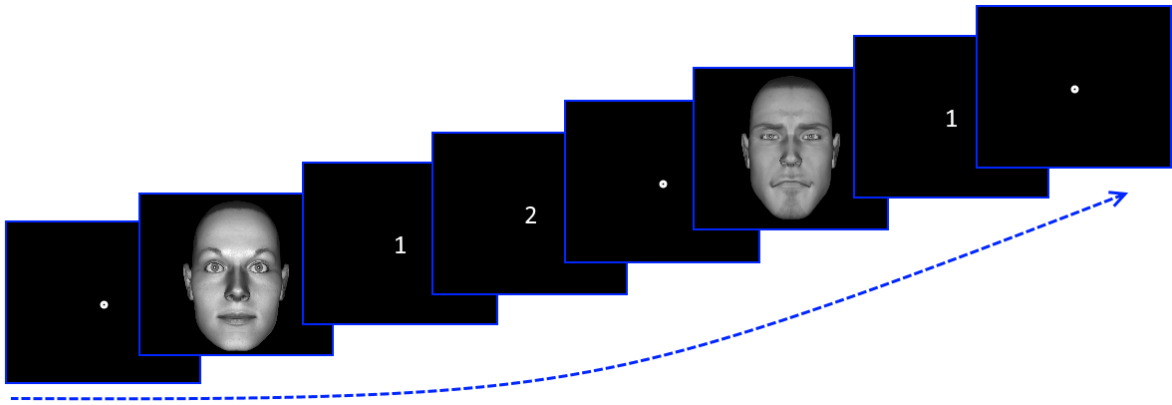
Figure 2: Stimuli presentation.The first face is a target one, thus - if correctly answered - after the stimulus will appear the white 1 screen, where the subject has to identify the face as seen/unseen in the adaptation phase, followed by the white 2 screen, corresponding to the 'Is identical to the one seen before?' question. The second face is a non-target, thus - if correctly answered - only the white 1 screen will appear. Notice that between each stimulus is displayed a fixation point placed in the screen middle.
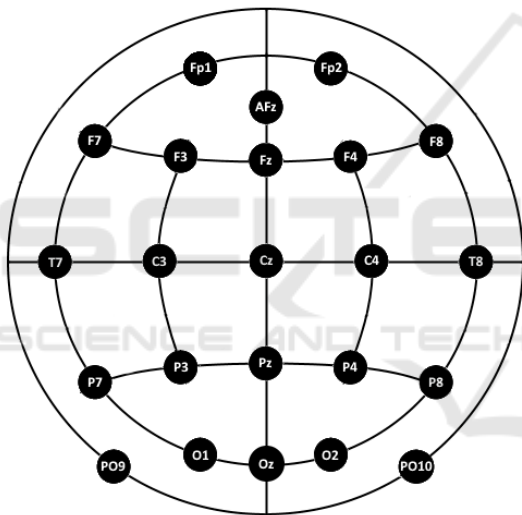


Figure 3: Electrode positions on the *EasyCap*, used in the experiment.

Each raw recording was processed following three main steps, beginning with a dataset initialization: import of the vhdr BrainRecorder file with bva plug-in for EEGLAB, channel editing and re-reference to the electrically neutral Cz sensor, removal of uninteresting track parts corresponding to the adaptation and trial phases and division of the total recording into the two experimental parts. Afterward the core signal processing procedure took place: the Hamming windowed sinc Finite Impulse Response (FIR) filter was run as a combination of low-pass and band-pass filters, cutting all the frequencies below and above 1 and 50Hz; in contrast to other literature works (Klados et al., 2011) (Radüntz et al., 2015) (Roy et al., 2013) (Scharinger et al., 2015) (Winkler et al., 2011), the up-

per bound was increased from 40 to 50Hz to prevent a too high suppression of the signal due to the following processing steps. Also, the filter range was justified by the fact that in the present study the rhythms, frequency bands, of interest were the alpha (8-13Hz), beta (13-30Hz) and gamma (30-100Hz) ones and the recording was performed over non-pathological subjects.

Having obtained a more clean signal, the Independent Component Analysis (ICA) computation was performed. In fact, the ICA model (Jung et al., 2000) was satisfied by the signal characteristics: the multi-channel recording was a mixture of brain activity and artifacts, the volume conduction was considered to be linear and instantaneous, the sources involving the noisy components were not generally time locked to the neural activity, the number of sources was equal to the number of sensors. The Independent Components (ICs) obtained from the previous computation were then inspected with the aid of SASICA extension for EEGLAB (Chaumon et al., 2015), which provided topoplots and statistics based on power spectrum, kurtosis and correlation with the ocular electrodes for artefactual components discrimination. After being identified, the ICs were removed from the FIR filtered signal. The eventually remaining artifacts (mostly spiky eye blinks) were manually pruned.

## 4 RESULTS AND DISCUSSION

For each subject, the sets of CIDT, CMODT, CNR and ERR events were collected. The signal portions corresponding to the 500 ms preceding the stimulus presentation were also collected and considered as

Table 2: For each channel and each rhythm the percentage of subjects that shows a significant variation in PSD comparing baseline and CIDT set (p-values < 0.05) is reported. The highest percentage of subjects reports a great variability in the alpha rhythm for parietal electrodes.

| Channel | Alpha | Beta | Gamma |
|---------|-------|------|-------|
| Fp1 | 41,18 | 41,18 | 11,76 |
| AFz | 35,29 | 23,53 | 11,76 |
| Fp2 | 41,18 | 29,41 | 23,53 |
| F7 | 41,18 | 41,18 | 23,53 |
| F3 | 47,06 | 35,29 | 11,76 |
| Fz | 41,18 | 35,29 | 11,76 |
| F4 | 52,94 | 29,41 | 17,65 |
| F8 | 41,18 | 29,41 | 23,53 |
| T7 | 35,29 | 41,18 | 17,65 |
| C3 | 47,06 | 47,06 | 23,53 |
| C4 | 35,29 | 17,65 | 23,53 |
| T8 | 47,06 | 17,65 | 11,76 |
| P7 | 41,18 | 52,94 | 23,53 |
| P3 | 58,82 | 52,94 | 23,53 |
| Pz | 52,94 | 47,06 | 23,53 |
| P4 | 52,94 | 41,18 | 11,76 |
| P8 | 47,06 | 17,65 | 11,76 |
| PO9 | 41,18 | 29,41 | 5,88 |
| O1 | 35,29 | 35,29 | 11,76 |
| Oz | 35,29 | 35,29 | 17,65 |
| O2 | 41,18 | 29,41 | 11,76 |
| PO10 | 41,18 | 29,41 | 11,76 |

Table 3: For each channel and each rhythm the percentage of subjects that shows a significant variation in PSD comparing baseline and CMODT set (p-values < 0.05) is reported. A percentage of subjects greater than 70% reports a great variability in the alpha rhythm for frontal electrodes.

| Channel | Alpha | Beta | Gamma |
|---------|-------|------|-------|
| Fp1 | 70,59 | 52,94 | 17,65 |
| AFz | 76,47 | 47,06 | 11,76 |
| Fp2 | 70,59 | 52,94 | 11,76 |
| F7 | 70,59 | 41,18 | 23,53 |
| F3 | 70,59 | 52,94 | 11,76 |
| Fz | 70,59 | 58,82 | 5,88 |
| F4 | 70,59 | 52,94 | 17,65 |
| F8 | 58,82 | 41,18 | 17,65 |
| T7 | 58,82 | 41,18 | 11,76 |
| C3 | 58,82 | 58,82 | 17,65 |
| C4 | 41,18 | 23,53 | 11,76 |
| T8 | 41,18 | 47,06 | 11,76 |
| P7 | 47,06 | 41,18 | 11,76 |
| P3 | 52,94 | 52,94 | 35,29 |
| Pz | 64,71 | 64,71 | 29,41 |
| P4 | 47,06 | 41,18 | 29,41 |
| P8 | 41,18 | 23,53 | 17,65 |
| PO9 | 47,06 | 47,06 | 17,65 |
| O1 | 47,06 | 35,29 | 17,65 |
| Oz | 52,94 | 41,18 | 29,41 |
| O2 | 58,82 | 35,29 | 23,53 |
| PO10 | 47,06 | 35,29 | 29,41 |

Table 4: For each channel and each rhythm the percentage of subjects that shows a significant variation in PSD comparing baseline and CNR set (p-values < 0.05) is reported. About 90% of subjects reports a great variability in the alpha rhythm for frontal electrodes.

| Channel | Alpha | Beta | Gamma |
|---------|-------|------|-------|
| Fp1 | 94,12 | 64,71 | 35,29 |
| AFz | 94,12 | 70,59 | 23,53 |
| Fp2 | 94,12 | 70,59 | 29,41 |
| F7 | 88,24 | 58,82 | 29,41 |
| F3 | 88,24 | 52,94 | 17,65 |
| Fz | 88,24 | 64,71 | 23,53 |
| F4 | 88,24 | 64,71 | 35,29 |
| F8 | 94,12 | 70,59 | 29,41 |
| T7 | 82,35 | 70,59 | 35,29 |
| C3 | 94,12 | 88,24 | 41,18 |
| C4 | 64,71 | 47,06 | 23,53 |
| T8 | 88,24 | 64,71 | 23,53 |
| P7 | 58,82 | 58,82 | 29,41 |
| P3 | 76,47 | 82,35 | 41,18 |
| Pz | 88,24 | 88,24 | 29,41 |
| P4 | 70,59 | 64,71 | 23,53 |
| P8 | 82,35 | 52,94 | 23,53 |
| PO9 | 70,59 | 52,94 | 29,41 |
| O1 | 76,47 | 58,82 | 35,29 |
| Oz | 76,47 | 64,71 | 29,41 |
| O2 | 64,71 | 58,82 | 35,29 |
| PO10 | 88,24 | 58,82 | 29,41 |

Table 5: For each channel and each rhythm the percentage of subjects that shows a significant variation in PSD comparing baseline and ERR set (p-values < 0.05) is reported. About 90% of subjects reports a great variability in the alpha rhythm especially for frontal and parietal electrodes, and about 80% in the beta rhythm for the same electrodes.

| Channel | Alpha | Beta | Gamma |
|---------|-------|------|-------|
| Fp1 | 94,12 | 70,59 | 17,65 |
| AFz | 88,24 | 64,71 | 23,53 |
| Fp2 | 94,12 | 70,59 | 23,53 |
| F7 | 94,12 | 76,47 | 35,29 |
| F3 | 94,12 | 76,47 | 17,65 |
| Fz | 88,24 | 70,59 | 23,53 |
| F4 | 82,35 | 64,71 | 35,29 |
| F8 | 88,24 | 82,35 | 35,29 |
| T7 | 100,00 | 82,35 | 41,18 |
| C3 | 82,35 | 76,47 | 41,18 |
| C4 | 64,71 | 52,94 | 23,53 |
| T8 | 82,35 | 58,82 | 17,65 |
| P7 | 58,82 | 64,71 | 35,29 |
| P3 | 76,47 | 88,24 | 47,06 |
| Pz | 88,24 | 76,47 | 29,41 |
| P4 | 76,47 | 64,71 | 29,41 |
| P8 | 88,24 | 52,94 | 17,65 |
| PO9 | 70,59 | 64,71 | 35,29 |
| O1 | 58,82 | 52,94 | 35,29 |
| Oz | 58,82 | 47,06 | 41,18 |
| O2 | 70,59 | 52,94 | 29,41 |
| PO10 | 70,59 | 58,82 | 17,65 |

baseline. During this time interval the fixation point was shown. The PSD of the events of each set was estimated using the Welch's method for each subject, and each electrode. Also the PSD of the corresponding baselines were evaluated. One-way ANalysis Of Variance (ANOVA) was then applied for each of the three rhythms of interest, i.e. alpha, beta and gamma, to determine significant brain activity variations between baseline and each of the four types of events. This analysis was performed for each subject and electrode. In Tables 2-5 the percentage of subjects that shows a significant variation in PSD ($p-value < 0.05$) was reported for each electrode and rhythm, for CIDT, CMODT, CNR, and ERR events respectively. These percentages were in general higher for alpha and beta rhythms, in particular for CNR events (correct identification of non-target stimulus) and erroneous answers (ERR) and were more evident in the frontal or parietal electrodes. In case of CIDT events (correct identification of neutral basic target stimulus) it seems that the variation of brain activity with respect to the baseline was less evident.

## 5 CONCLUSIONS

Differences were found in the EEG patterns when recognizing neutral target faces versus faces modified with biological plausible changes. In particular brain activity changes were mainly found for alpha and beta rhythms in frontal and parietal areas. The analysis on this database can be useful as baseline for further studies on people affected by congenital prosopagnosia or autism performing the same experiment, having identified the brain activities variation in a healthy population. This preliminary analysis can be strengthened to better distinguish between the four different types of events, taking into account more features to describe the EEG patterns, besides the PSD here considered. Moreover, to better compare results from different subjects, proper data normalization has to be addressed, such as subtracting the average power recorded on the scalp or standardize the sensors voltage by using the z-score.

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