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Detection of Familiar and Unfamiliar faces from EEG

Navin Vanzara[1], Chintan Shah[1*], Avani Vithalani[2]

[1]Biomedical Engineering Department, [2]Electronics and Communication Engineering Department, Government Engineering College, Sector-28, Gandhinagar, Gujarat, India

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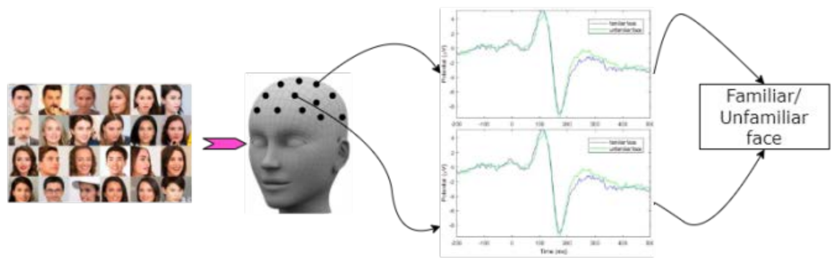
ABSTRACT



Face recognition is a complex cognitive task that involves a distributed network of neural sources. While some components of this network have been identified, the temporal sequence of these components is not well understood yet. This study contains the detection of familiar or unfamiliar faces by using the event-related potential (ERP) response from the recorded EEG signal from subjects when they were introduced to stimulus as familiar faces, unfamiliar faces and scrambled faces, this study includes the dataset which contain the EEG data from 18 subjects for face recognition task, this recorded data is being used to detect if there is any significant difference recorded EEG data for type of faces. ERP artifacts based on the variance of components decomposed by PCA, the results achieved by using ICA and SPA then compared with each other to make the exact and accurate decision on the EEG response for a familiar face and unfamiliar faces.

Keywords: Face perception, ICA decomposition, EEGLAB (MATLAB extension), SPA, Independent T-test

INTRODUCTION

The Facial perception is an individual's understanding and interpretation of the face.[1] For the social cognition, face perception plays an important part. The ability to observe and interpret faces with extra information such as identity, mood, age, sex, and race has allowed us to develop facial recognition over time. This ability has helped individuals to shape how they interact with one another and comprehend their immediate environment.[2]

Numerous studies have been conducted on early development as the time whenever the brain first begins to distinguish between faces and other items. It is still unclear when individuals acquire the potential to recognize well-known faces since studies have produced contradicting results and because it may rely on a variety of parameters, such as the ongoing emergence of a specific face through time.

*Dr. Chintan Shah, Biomedical Engineering Department, Government Engineering College, Sec-28, Gandhinagar
Email: cpshah@gecg28.ac.in

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The acquisition of visual perception depends on perceptual experience, which includes the capacity to identify and classify well-known faces and interpret their emotions. The neural networks that underlie face perception in infants are comparable to those in adults, but imaging technologies that are safe to use on children have their disadvantages when it comes to retrieving specific information from subcortical brain regions that are active and involved in adult facial perception. Those certain regions also showed activity close to the fusiform gyrus.

Adults who often process faces using subcortical pathways. If they were exposed to stimuli in the form of images of macaque monkeys throughout this time period, newborns whom can identify and distinguish between monkey faces at about 6 months of age were more likely to preserve this capacity.[2]

A Humans are extremely good at remembering faces. Face processing is extremely quick and efficient and is very helpful to identify any faces, whether they have been familiar or unfamiliar. Numerous brain regions appear to be involved in the processing of faces, including the inferotemporal cortex, fusiform face area, occipital face area, and superior temporal sulcus. Each of them performs somewhat distinct tasks that, when combined, aid in the challenges the process confronts.[2–4] which includes fusiform face area (FFA), Occipital face area (OFA), and Superior temporal sulcus (STS). In the lateral fusiform gyrus is where FFA is situated[4].

According to research, FFA analyzes faces systemically and is sensitive to the existence of facial components as well as their placement and their specific shape or layout. Processing face detection and identification requires the FFA. The Occipital Face Area (OFA) is situated next to the inferior occipital gyrus on the lateral surface of the occipital lobe.[3] Similar to the fusiform face region, which is active during face recognition and detection, is this area. The STS, which is not sensitive to the arrangement of these features, is involved in the classification of face parts. Furthermore, research have shown that STS region is in charge of gaze perception.[5] Most of the action potentials during face perception occur bilaterally in the extrastriate area, especially in the three areas mentioned above. Researchers contend that in most cases, higher activity on one side over another, such as the FFA, is more crucial for processing facial information.[6]

The brain's measurable reaction to a specific sensory, cognitive, or motor event is known as an event-related potential (ERP).[7] The EEG records thousands of brain functions that are happening at once. As a result, the EEG recording of a single trial seldom shows the brain's reaction to a particular stimulus or event of interest. The investigator must run several trials and average the findings in order to see the brain's reaction to a particular event or stimulus. The widely investigated issue in cognitive neuroscience using electroencephalography is event related potentials (ERPs) (EEG). Over the course of decades of research, a variety of cognitive activities and moods have been related to several distinct ERPs components.[7]

When we reason about other people and try to comprehend them, we primarily use the information provided by the face to help us decide how to behave and react to our environment. In the uncommon syndrome known as acquired prosopagnosia, a person is unable to distinguish between the faces of familiar and unknown persons. There is evidence that the brain processes familiar and new features differently. This study uses the subject's recorded EEG data to look for any changes in brain activity when they observe familiar or new faces. With this study, we are testing the hypothesis that when we see faces, the brain will react to them. The brain should react more quickly to familiar faces, and it should also produce a different EEG signal than it does when processing unfamiliar faces, so different types or characteristics of signal should be found for both types of face processing.

Literature Review

Various scholars shared their perspectives on face perception, outlining its limitations as well as their primary points of view and significant findings from earlier studies. The FFA is involved in face detection and face identification, however there is conflicting data regarding its function in discriminating among familiar and unfamiliar faces or in emotional expressions on faces,[2] Inverted faces are represented by more generic object recognition processes, whereas upright faces are represented by mechanisms designed specifically for upright faces[8], Rapid face and scene recognition and memory indicates that category-specific computational hubs in the ventral visual stream are cooperating with the diffuse cortical memory network.[9] It also replicates previous results from EEG and demonstrates that MEG provides similar signal-to-noise ratios for face-selective FPVS responses as EEG using the rapid periodic visual stimulation (FPVS) paradigm using combined EEG and MEG data gathering technology,[10] Additionally, it has been shown that preprocessing is important to standardize the data into a form that allows us to comprehend it while keeping as much of the significant signal as possible,[11] The EEG signal used to filter the data may be cleaned up using a variety of methods.[12] Numerous studies demonstrate that large bilateral Extrastriate activations occur during face perception, especially in the fusiform face region, occipital face area, and superior temporal sulcus. Additionally, there are numerous ways to overcome the inverse problem of source separation from faces. Data collected from the studies' EEG[12]. There are many distinct types of sources in the brain that appear at various types of sources, in various brain areas, and at various time frames. Since all of these sources are mixed together, they must be separated in order to be examined independently from one another. All neuroscience researchers have concentrated on attempting to comprehend the non-stationary aspect of the brain since brain time series data are very non-stationary,[13] Bind source separation (BSS), which is the separation of a set of source signals from a collection of mixed signals with very little knowledge about the source signals, is another name for this issue,[13] All investigations that were conducted over years of research on this inverse topic have provided valuable information which should be taken into account when pursuing the same line of inquiry. Examples include the preprocessing procedures that should be used on the subject's EEG raw data and the technique that may be used to more accurately examine the data in order to distinguish the source of interest from the mixed signals,[14] According to the literature, a number of strategies have been presented to address the source separation problem, however further research is needed to increase the accuracy of the findings for distinguishing the sources from mixed signals. The source separation problem is still open-ended or inconclusive.[15] Principal component analysis (PCA) and independent component analysis (ICA), two of the most popular and effective techniques, both perform well in the absence of echoes.[16]

Methodology and Experimental Setup

Techniques for blind source separation are frequently used to restrict the range of probable outcomes in a way that is unlikely to leave out the intended outcome because the major challenge of the inverse problem is indetermination, or the idea that there may be change even though it is not immediately observable. There are many approaches to addressing this problem, such as principal component analysis and independent component analysis, which primarily focus on source signals that are minimally correlated or maximally independent in a non-deterministic manner and are based on the probability theory or the notion that randomness can aid in the prediction of the future course of events. Another technique is nonnegative matrix factorization. To demonstrate independent component analysis (ICA), which is primarily focused on sources signals that are minimally correlated or maximally independent in a non-deterministic way, single trial PCA-based artefact removal (SPA), which is based on variance distribution separation to distinguish between artifacts and neural activity, is used in this study.

Experimental Design and Dataset

The Declaration of Helsinki was observed in each and every phase of this dataset's recording (1964). All Participants accepted an offer to take part in this experiment or research and were member of the MRC Cognition & Brain Sciences Unit participant panel. There were 19 participants in this study, including 8 female and 11 male participants ranging in age from 23 to 37. The study was approved by the psychological ethics committee at Cambridge University.[17]

The basic design of the experiment is as follows:

Stimuli were projected onto a screen which is approximately 1.3 m in front of the participant, and subtending horizontal and vertical visual angles of approximately 3.66° and 5.38° respectively. The photographs or stimuli were presented against a black background, with a white fixation cross in the center of the photographs. The interstimulus interval contains a central white circle for 1,700 ms and Participants were advised to fixate centrally during the experiment, this change from central circle to central cross was helping those participants to prepared for each stimulus before that stimulus was presented. They were also instructed to try to not blink during the cross-hair or stimulus and they can blink freely during the circle. EEG data was measured in a light magnetically shielded room by using an Elekta Neuro-mag Vector view 306 system. A 70 channel Easy cap with 10/10 Motage system was used to record the EEG data at the same time. A 3D digitizer was used to record the locations of the EEG electrodes on the scalp during the experiment.

In addition to 150 greyscale photos of the scrambled faces, which are not included in this study because it primarily focuses on the distinction between familiar and unfamiliar brain activity, each face stimulus contains two sets of 300 greyscale photographs, half of which are of familiar or famous people and the other half of which are of unknown, unfamous people to participants. All images were matched, then cropped to only display faces.

Pre-Processing steps

Recorded raw EEG data was being cleared and filtered before processing the data for the study, those pre-processing steps includes[11]:

1. Extracting EEG channels out of the MEG/EEG data,
2. Adding fiducials,
3. Extracting events from event channel,
4. Correcting event latencies (events have a shift of 34 ms),
5. Resampling data to 250 Hz (To lightweight the dataset size),
6. Re-referencing the data,
7. Applied Clean line step to remove the line noise from the data,
8. Applied ASR to Reject bad channel, Removal of bad data periods.

As such step applied to the raw EEG data to pre-process the data before applying source separation methods such as ICA and SPA. All the preprocessing step were performed using EEGLAB platform which is MATLAB extension[18]. After pre-processing the data was ready to make ERP study.

Independent Component Analysis (ICA)

The original data has many different types of individual sources mixed together, ICA used to separate all those individual sources and to obtain isolated sources of each independent component[19,20].

ICA converts mixed EEG recording into unmixed EEG recording of each individual component or each individual channel[21].

There are two key assumptions in ICA, such as:

The hidden independent components that being uncover must be,

1. Statistically independent.
2. Non-gaussian.

Assume that we have n mixtures of $x_1, x_2, .., x_n$ of n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + ... + a_{jn}s_n \quad (1)$$

The time index t has dropped in ICA model, since as per assumption that each mixture and individual components are random variables instead of a proper time signals, thus observed values x(t), e.g., the EEG signals recorded in this dataset as the sample of this random variable.

Without loss of generality, here we can assume that both the mixture variables and independent component have zero-mean.

If this is not true, then the observable variable x_j can be centered by subtracting the sample mean, which makes the model zero-mean.

The equation can be expressed using vector-matrix notation,

$$x = As \quad (2)$$

where,

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, s = \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix} \text{ and}$$

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix}$$

where,

x= Random vector whose elements are the mixtures $x_1, x_2, ..., x_n$,

s = Random vector whose elements are the sources $s_1, s_2, ..., s_n$,

A = mixing matrix with elements a_{ij}

Expression in columns of matrix A,

$$x = \sum_{i=1}^{n} a_i s_i \quad (3)$$

As per derived Eq. (3) statical model is called independent component analysis or ICA model.

Single Trail PCA Based Artifact Removal (SPA)

The core computation is based on PCA, but the algorithms for identifying the artifacts components and data processing is changed in order to reduce computational cost.

The main idea of principal component analysis (PCA) is to reduce the dimensionality of the dataset which contains large number of interrelated variables, and try to obtain or retaining as much as possible of the variation present in the in the dataset[22]. his can be achieved by transforming to a new set of variables, such as principal components (PCs), which are uncorrelated, and which are ordered in a manner so that the first few obtained variation present in most of the variable. PCA uses up to second order moments of the data to produce uncorrelated components.[14]

Let's assume that we have sample of n observations, each of the observations with the p variables:

$$x = (x_1, x_2, x_3, x_4, \ldots\ldots, x_p)$$

To determine the first principal component:

$$z_1 \equiv a_1^T x = \sum_{i=1}^{p} a_{i1} x_i \quad (4)$$

where,

Vector $a_1 = (a_{11}, a_{21}, a_{31}, ., ., a_{p1})$ $St.var[z_1]$ is a maximum.

K^{th} Principal component will be derived as according to the Eq. (4):

$$z_k \equiv a_k^T x = \sum_{i=1}^{p} a_{i1} x_i \quad (5)$$

Where vector $a_k = (a_{1k}, a_{2k}, \ldots\ldots, a_{pk})$ $St.var[z_k]$ is a maximum.

Subject to: $Cov[z_{k,} z_l] = 0 \; for\; k > l \geq 1$ and $a_k^T a_k = 1$.

By computing the principal components, we can use it to perform the change of the basis on the data, sometimes using only first few principal components and ignoring the rest.

Results and Discussion

To find the difference between the brains activity when a subject is provided with the familiar or unfamiliar face images as stimuli. here in this study, we have used ERP study on recorded EEG data and by EEGLAB software which is an extension platform for MATLAB environment.

For the ERP study we have used the ICA and SPA method to extract features from the data as well as to compare results from the both methods to find the more reliable interpretation on the results.

This chapter will commence by presenting the sample demographic data to understand the composition and representativeness of the samples brain activity as how the brain reacts toward the familiar faces than to the unfamiliar.

the data recorded for 19 subjects but according to the dataset instruction there were some of the subjects in which the EEG was not properly recorded, thus in this study there are only selected recorded dataset being used for the analysis and those sample demographics are as follows:

1. 10 subjects selected for the data analysis, as few of recorded EEG data was containing too much of noise by head moments.
2. Half of them were male and half of them were female subject in this analysis.
3. All subject is having the age range of 23- to 32-year-old.
4. All subject were from Caucasian, who had spent many years in the UK.

By using the recorded EEG data from those selected subjects when face stimuli onset we can average out the brain activity for type of stimuli and we can detect if there is any significant different between the brain's response when processing familiar faces or unfamiliar faces. To illustrate all the results which can be obtain from these data, and validate the basic data quality, here report an ERP data analyses on a subset of 10 selected subjects. To analyze the EEG data, we have used EEGLAB with MATLAB platform. The continuous data in each run was first epoched from −500 to +1,200 ms around the onset of each stimulus. Across participants, between 880 and 889 epochs were extracted.

These epochs were then lowpass filtered to 32 Hz, removing the initial and final 400 ms to accommodate filter artifacts and then averaging the remaining trials for each of the two conditions (range across participants and conditions of remaining valid trials was 225 to 296, median=280).

Descriptive Statistics

In the dataset there are basically three different categories of the stimulus provided to the subject as familiar faces, unfamiliar faces and scrambled faces. Here, this research is mainly focused in detecting difference in the brains activity when processing familiar faces and unfamiliar faces thus only these two types of signals being used for analysis and going to ignore the data representing the brains activity for scrambled faces.

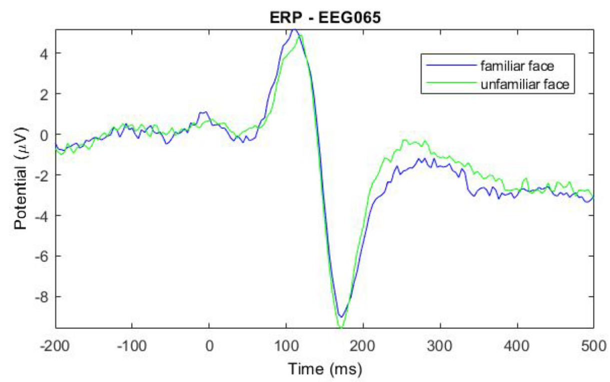

Figure 1: Grand average of ERPs for types of stimuli at a right posterior electrode.

Figure 1 shows the grand average of Event Related Potential (ERP) which was generated from a right parieto-occipital electrode (EEG065) using ICA to the EEG dataset. A negative bend peaking around at 170 ms which is also known as 'N170' component, it does not show any significant difference for familiar and unfamiliar faces. But at around 250 ms, there is a slower potential shift observed for familiar and unfamiliar faces until the end of the epoch.

According to the ERP data generated across all participants using ICA algorithms, for comparing those data with the results generated using SPA algorithms we have selected 10 participants ([1]M1 to [2]F5) for this comparison, because ICA provides group data analysis but in case of SPA it can only applied to the individual subject EEG data at a time. Thus, to compare results from both algorithms event related potentials reading was generated for individual subject using both algorithms and compared those event related potentials readings to make more reliable intuitions. Reading from the individual subject for ICA & SPA are represented using bar graph charts which are listed accordingly below;

1. Event related potentials (ERPs) from electrode placed on right parietal lobe and the brain activity detected on 170 ms from stimulus onset using ICA and SPA.

[1] M1 = 1^{st} Male subject
[2] F5 = 5^{th} Female subject

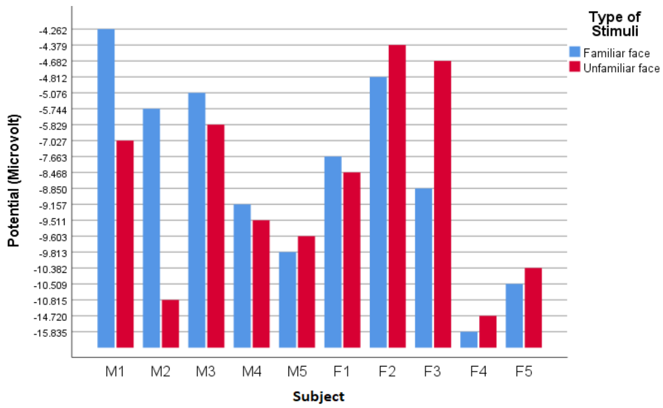

Figure 2: ERP data from EEG065 (Right parietal lobe) at 170 ms using ICA

Table 1: Group Statistics of ERP data from EEG065 at 170 ms using ICA

	Face Type	N	Mean (µv)	Std. Deviation	Std. Error Mean
Potential (Microvolt)	Familiar Face	10	-8.172	3.505	1.108
	Unfamiliar Face	10	-8.541	3.174	1.003

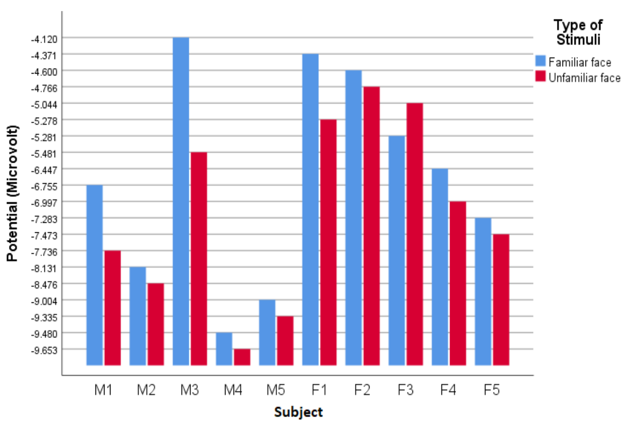

Figure 3: ERP data from EEG065 (Right parietal lobe) at 170 ms using SPA

Table 2: Group Statistics of ERP data from EEG065 at 170 ms using SPA

	Face Type	N	Mean (µv)	Std. Deviation	Std. Error Mean
Potential (Microvolt)	Familiar Face	10	-6.547	1.936	.612
	Unfamiliar Face	10	-7.023	1.811	.572

2. Event related potentials (ERPs) from electrode placed on right parietal lobe and the brain activity detected on 250 ms from stimulus onset using ICA and SPA.

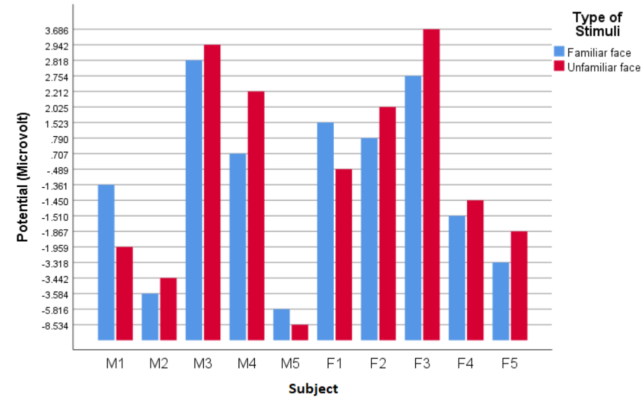

Figure 4: ERP data from EEG065 (Right parietal lobe) at 250 ms using ICA

Table 3: Group Statistics of ERP data from EEG065 at 250 ms using ICA

	Face Type	N	Mean (µv)	Std. Deviation	Std. Error Mean
Potential (Microvolt)	Familiar Face	10	-.699	2.903	.918
	Unfamiliar Face	10	-.687	3.664	1.158

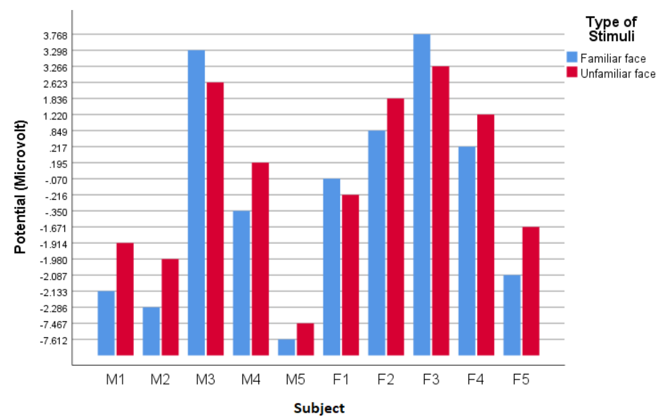

Figure 5: ERP data from EEG065 (Right parietal lobe) at 250 ms using SPA

Table 4: Group Statistics of ERP data from EEG065 at 250 ms using SPA

	Face Type	N	Mean (µv)	Std. Deviation	Std. Error Mean
Potential (Microvolt)	Familiar Face	10	-.640	3.230	1.021
	Unfamiliar Face	10	-.410	3.107	.982

Inferential statistics

In this section the inferential statistics being used for two main purposes as to making the estimates about the populations and to test the hypothesis to draw a reliable conclusion about the populations. Here in this study, we have used independent T-test to make the estimate about the ERP data generated from this research.

As to find the difference between two type of groups as familiar and unfamiliar face processing response from the data, independent T-test method applied to the sampled data as follows:

1. Independent T-test applied to the ERP data from electrode placed on right parietal lobe and the brain activity detected on 170 ms from stimulus onset using ICA and SPA.

Table 5: Independent T-test on data from EEG065 at 170ms using ICA

Independent Sample Test							
Levene's T-test for Equality of Variances				T-test for Equality of Means			
		f	Sig.	t	df	Sig. (2-tailed)	
Potential	Equal variances assumed	.05	.826	.247	18	.808	
	Equal variances not assumed			.247	17.8	.808	

Table 6: Independent T-test on data from EEG065 at 170ms using SPA

Independent Sample Test						
Levene's T-test for Equality of Variances				T-test for Equality of Means		
		f	Sig.	t	df	Sig. (2-tailed)
Potential	Equal variances assumed	.03	.826	.569	18	.577
	Equal variances not assumed			.569	17.9	.577

2. Independent T-test applied to the ERP data from electrode placed on right parietal lobe and the brain activity detected on 250 ms from stimulus onset using ICA and SPA.

Table 7: Independent T-test on data from EEG065 at 250ms using ICA

Independent Sample Test						
Levene's T-test for Equality of Variances				T-test for Equality of Means		
		f	Sig.	t	df	Sig. (2-tailed)
Potential	Equal variances assumed	.17	.683	-.008	18	.994
	Equal variances not assumed			-.569	17.1	.994

Table 8: Independent T-test on data from EEG065 at 250ms using ICA

Independent Sample Test						
Levene's T-test for Equality of Variances				T-test for Equality of Means		
		f	Sig.	t	df	Sig. (2-tailed)
Potential	Equal variances assumed	.001	.971	-.162	18	.873
	Equal variances not assumed			-.162	17.9	.873

From table 5, 6, 7 and 8, we can see that T-test results for the ERP data recorded from type of stimulus and for the ICA and SPA used to generate the electrical potential and by the level of significant we can say if there is any significant difference in the brain response while processing familiar faces or unfamiliar faces.

In the hypothesis statement we were trying to detect if there is any significant difference between the brains activity in order to process familiar faces or unfamiliar faces to test this hypothesis, we have used the independent sample T-test, independent sample T-test assumes that variance of the sample groups is approximately equal by use of levene's test of equality of variance, it tests the assumption of the homogeneity of the variance. But the level of significance (α) is greater than 0.05 for the independent sample T-test for all the trail for 170ms component and for the 250ms component as shown in the table 5, 6, 7 and 8.

Hence, with the 95% of confidence, we cannot say that, there is significant difference between the EEG signal generated from the right parietal lobe when processing familiar faces or unfamiliar faces.

Conclusions

In this research work, we have used independent component analysis (ICA) and Single trial PCA based artifact removal methods to extract the ERP featured data from the recorded EEG signals from the subjects. We have averaged out each trial reposed from all the epochs for familiar faces and for unfamiliar faces. By using the independent t-test statistical analysis on the sampled ERP data we can say that there is no significant difference between EEG recorded from right parietal lobe when processing familiar faces or unfamiliar faces. In the study we have shown the ERP data for only one electrode on different time window as for 170ms as well as for 250 ms to find the consistent change for the same but according to independent T-test results indicates that it is statistically inconsistent in the both algorithms, also this same procedure applied to different electrode on the right parietal lobe as well but results were same. However, there is difference between the ERP data generated using ICA and SPA, and as in the independent T-test method the results were quite different for the ERP data recorded using ICA compare to SPA, although there is a pattern in most of the subject with their recorded event related potential as it is more negative when processing unfamiliar faces than familiar faces but this change is not statistically significant, It is proven that there is a difference in processing familiar faces compared to unfamiliar ones because of all the electrical potential readings produced by both algorithms; there is roughly ±0.5 μv difference between the means for familiar and unfamiliar faces.

There are few factors which may have affected the data of interest while processing familiar face or unfamiliar faces, those factors are listed as follows:

1. Age and gender of the subject may affect the EEG data.
2. Neuroplasticity may different for each subject to process facial feature which results in change in event related potential.
3. The N170 ms component may different at $\pm 10\ ms\ to \pm 20\ ms$ and it changes person to person, so on the exact N170 component we may have lose the important data.

Future Work

Here, we used two different algorithms, ICA and SPA, to interpret the brain's activity for different types of faces. In future work, we hope to apply another algorithm, LIMO (Linear Modelling), which is also a MATLAB toolbox (compatible with EEGLAB), to analyze evoked responses over all space and time dimensions during the trials and try to find more data for the face perception and test them with all different types of feature extraction algorithms to make more reliably.

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Conflict of Interest

Authors declare no conflict of interest (academic, financial or other) is there for publication of this work.

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