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Analyses of The P300 Event Related Potentials in EEG Signals Using Shape-based Kernel: Fixed and Random Analyses Approach

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ABSTRACT

Several analyses methods have been investigated to accurately detect the P300 component. The P300 is the most prominent component that can be observed in the Event Related Potentials in EEG signals. It can be elicited in the brain as a person's reaction to a salient stimulus. The P300 signal has been used in different application such as lie detection and Brain-Computer Interface. In such applications, it is crucial to select an appropriate analysis technique that provides the most accurate classification for the data. In this paper, a method based on the shape of a typical P300 waveform is investigated to classify EEG data. The findings concluded that the shape-based weighted kernel provides more appropriate and accurate tool for detecting P300 in EEG-based lie detection.

Key words: P300, EEG signals, Random effect analyses,

1 INTRODUCTION

The brain is the basic part of an intricate system called *the Nervous System (NS)* that enables us to communicate with our environment. It is subdivided into two major components: *the Central Nervous System* (CNS) and *the peripheral nervous system* (PNS) [1]. The CNS is the most fundamental centre for processing information . It consists of the brain and spinal cord, with both components consisting of a vast collection of prominent cells known as *neurons,* the most fundamental unit in the nervous system. In general, three groups of neurons make up the nervous system: *sensory neurons, interneurons,* and *motor neurons*. *The sensory neurons* are responsible for detecting a stimulus from our environment (e.g., sound, light) and sending this stimulus as a message to the ***interneurons***. The interneurons then process the message and produce instructions that explain the response to that stimulus. These instructions are then sent to the motor neurons thorough the PNS. The *motor neurons* stimulate muscles to generate the appropriate response. They also stimulate the body's glands to produce hormones [2].

In fact, due to the huge number of neurons, the brain processes a high number of tasks at a specific time. For many years scientists have studied the brain deeply to understand the complexity of how it works, and now due to the technical progress in the last decade, scientists have become able of monitoring its functioning [3]. Different types of imaging techniques enable scientists to detect the exact part of the brain responsible for each function, such as thinking, emotions, or attention. One of the most commonly used brain imaging techniques, *electroencephalography* (EEG). In fact, different types of the brain imaging method are commonly used in some fields such as magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI), each of which has been devised for specific functions.

1.1 Electroencephalography (EEG)

The main purpose of the EEG is to record neural activity in the brain at a given time. One of the first techniques used for monitoring brain electrical signals, it was first used in 1929 by Hans Berger [1]. Many scientists have used the EEG to study different brain tasks such as emotion, thinking, and attention [4] [5].
It works by placing a set of electrodes at specific locations on the scalp. The number of electrodes varies due to the nature and the goals of the experiment (a standard 10-20 system (EEG) is shown on figure 1). These electrodes are usually connected to a computer to display the brain signals during a given task in the experiment.
In fact, the EEG has many advantages over other brain imaging techniques such as affordability and portability, which have led it to be used commonly for research. In spite of the fact that it has *poor resolution*, it offers a *high temporal resolution,* which enables the observer to study the neural activity that is locked to a specific stimulus more deeply. Another aspect the EEG offers is the ability to record brain activity directly without the need to monitor blood flow, as the fMRI and MRI requires [6].

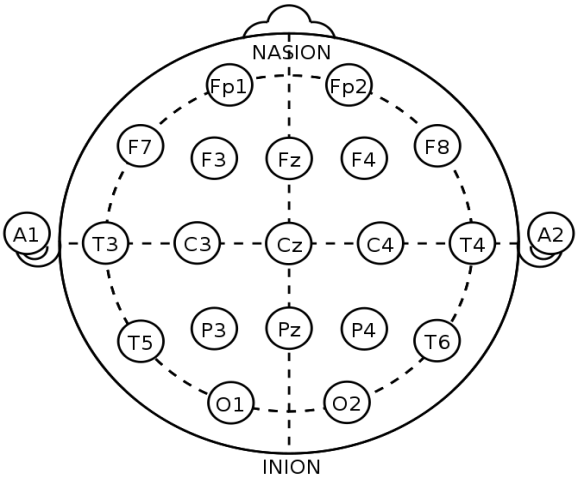

Figure 1: Standard 10-20 system (EEG) design.
Electrodes are distributed over five areas (frontal, central, parietal, occipital, temporal). They are named by letters and numbers (the letter refers to the first letter of the area name, while odd numbers refer to the left side, even numbers indicate the right side, and Z refers to zero or the midline area [7].

1.2 Event-related potentials (ERPs)

ERP can be defined as an average of brain response during a mental task (e.g., thought, attention) [8]. As mentioned earlier, the brain's response to a salient stimulus can be measured by using EEG. In a BCI experiment, a stimulus is presented repeatedly and the EEG measures resulting from the presentation are averaged together, producing ERPs [9]–[11]. In fact, a stimulus is presented repeatedly during the experiment, due to the large amount of noise in the EEG data recorded from a single presentation for a stimulus. Instead, some EEG segments that are time locked to the onset of stimulus are averaged together to make an ERP waveform.

1.2.1 The P300

The P300 signal is the most prominent component that can be observed in the ERP waveform [12], [13]. It can be elicited in the brain as a person's reaction to a salient stimulus. It is shown on the ERP signal as a positive peak at around 300 ms from the onset of the desired stimulus.
The P300 can usually be measured by its amplitude, latency, and area on the scalp in which it was generated. The amplitude of the P300 generated from the central/posterior areas of the scalp is usually larger than from any other parts of the brain [14] [15]. However, the electrode 'Pz' often produces a clear P300 signal.
It is worth noting that some factors influence the P300's characteristics. It is believed that the target stimulus that has a low probability to occur can elicit a high P300 amplitude [16] [17]. The uncertainty of stimulus is also another factor that affects the eliciting of a P300 component, hence, desired stimuli are usually presented in a pseudo-random order. The number of distractor stimuli presented between the occurrences of two target stimuli, the target-to-target interval (TTI), also has an impact on the P300 amplitude. The longer TTI produces a larger P300 amplitude [18].

1.3 Steady-State Visual Evoked Potentials (SSVEP)

SSVEPs are the brain's responses to a flickering stimulus presented repeatedly at a certain frequency, usually generated when visual stimuli are rapidly presented at frequencies higher than 6 Hz [19][20]. The amplitude of the SSVEP raises when the brain responds to a salient visual stimulus; thus, the SSVEP component can be used as a reliable measure to detect a target visual stimulus [21].

1.4 EEG Experiment and Data Collection

The EEG data used in this paper was taken from the lie detector EEG-based experiment that was fully explained in [22], [23]. Briefly, Twelve participants undertook the experiment. They were presented with three different types of stimuli. All stimuli were presented on a 20 LCD screen using Rapid Serial Visual Presentation (RSVP). Three critical stimuli were presented called Probe, Fake and Catch. Critical stimuli could be the participant's real birthday (*Probe*), their fake birthday (*Fake*), or a birthday that was not known to the participant (*Catch)*. Participants chose one birthday as their *Fake* birthday and were instructed that their task was to respond to that birthday, that is, in response to a yes/no question ('did you see your birthday?'), they were told to answer 'Yes'. They were told to answer 'No' to their real birthday (the *Probe)*. One birthday was chosen randomly and used as *Catch,* but participants were not aware of this.

1.5 Generating ERPs

In this experiment , participants are considered **guilty** when the P300 pattern produced for their real birthdays (Probe) significantly differs from the P300 pattern for irrelevant birthdays (Catches).
As this study is based on the P300 pattern, and because the P300 component can be observed within the ERP waveform, it is necessary to generate the ERP waveforms first. For each participant, three ERPs were generated: an ERP from *Fake* trials, an ERP from *Probe* trials, and an ERP from *Catch* trials.
In general, the ERP signal reflects voltage changes in brain activity , and is time-locked to the onset of a task-relevant stimulus. In our experiment, for instance, in order to generate an ERP for a fake birthday of a participant all trials containing fake birthdays are averaged together. As mentioned earlier, the amplitude of the P300 peak is larger

1.6 P300 Time Window

P300 is a positive peak that is produced at around 300 ms from the onset of a critical stimulus. Thus, the positive peak of the P300 was used as a basis to find the start and end of the P300. The following steps were used to find the start of the P300 time window:

1- Starting from 200 ms from the target onset, a 100ms time window is determined.
2- Sum all voltage changes in time-points in the determined window, and store the total.
3- The window then moves forward by 1 time point.
4- Repeat steps 2 and 3 until the start of the 100ms time window reaches 600ms from the target onset.
5- The start of the 100ms time window with the biggest total is considered as the start of the P300.

Whereas the following steps were used in finding the end of the P300 time window:

1- Starting from 800 ms from the target onset, a prior 100ms time window is determined.
2- Sum all voltage changes in time-points in the determined window, and store the total.
3- The window then moves backward by 1 time point.
4- Repeat steps 2 and 3 until the start of the 100ms time window reaches 600ms from the target onset.
5- The end of the 100ms time window with the smallest total is considered as the end of the P300.

Note, the inferential logic of our analysis method is to characterise an individual's P300 on the basis of *Fake* trials, where the largest P300s can be expected.

1.7 ERP Plots

Electrical brain responses for each participant are plotted in figures

- Black line: represents a participant's brain response to *Catch* (irrelevant) birthdays.
- Green line: represents a participant's brain response to his/her real (*Probe*) birthdays.
- Red line: represents a participant's brain response to his/her pretend (*Fake*)birthdays.

The first dashed line (from the left) refers to the start of the P300 of the *Fake* trials, while the second one refers to the end of the P300 of the *Fake* trials.

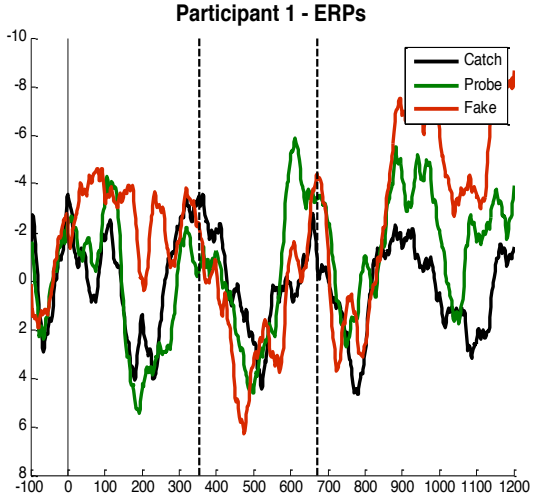

Figure 2 ERP of Participant 1

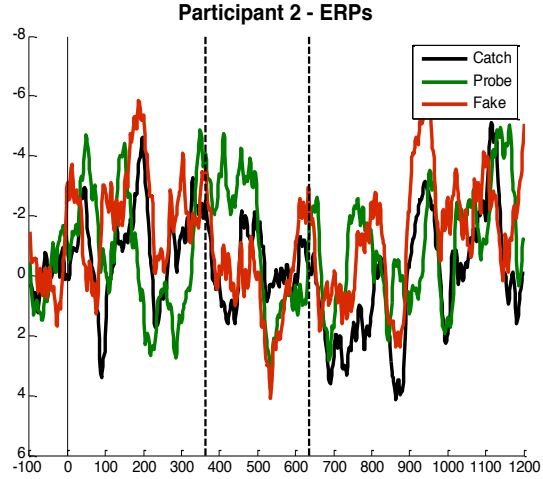

Figure 3 ERP of Participant 2

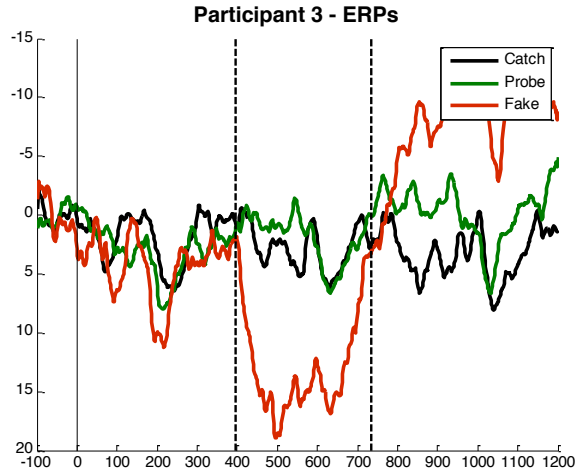

Figure 4 ERP of Participant 3

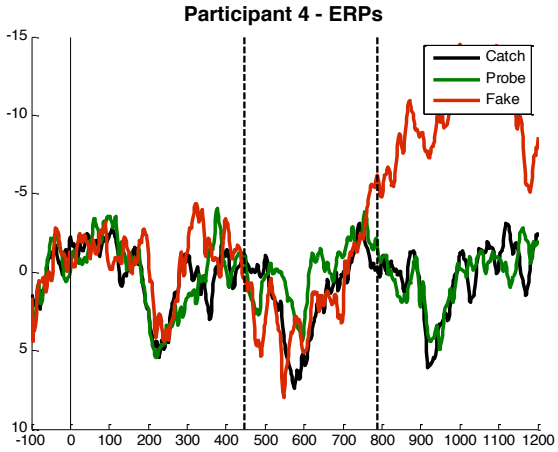

Figure 5 ERP of Participant 4

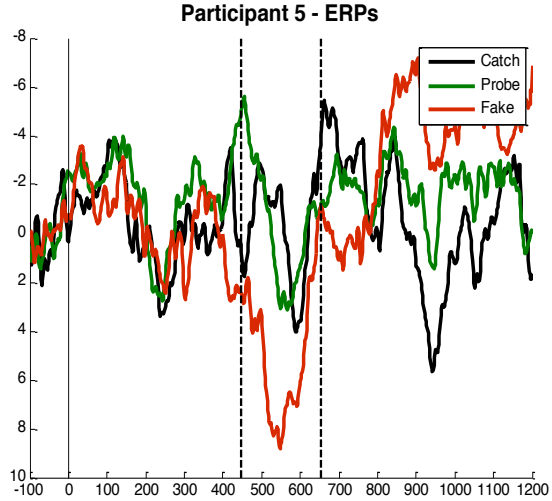

Figure 6 ERP of Participant 6

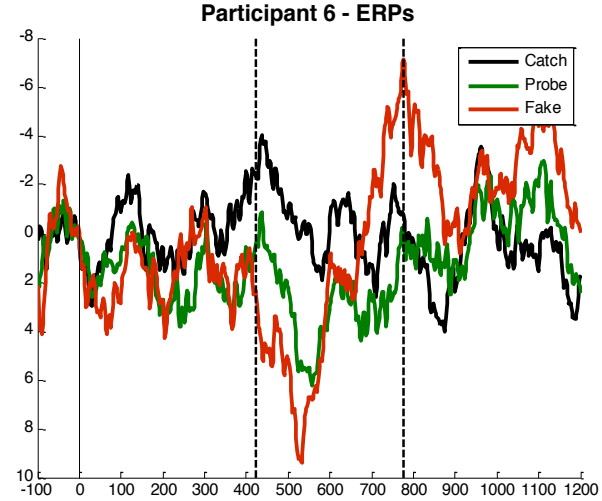

Figure 7 ERP of Participant 7

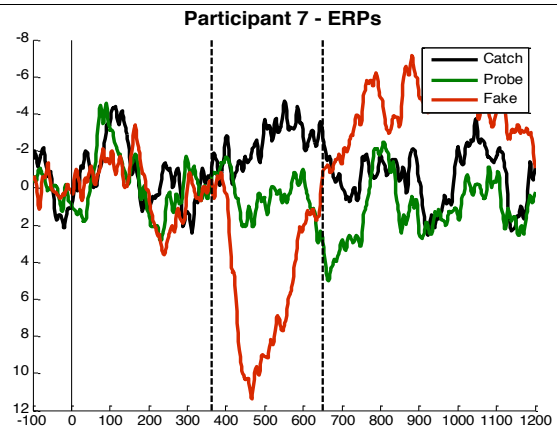

Figure 8 ERP of Participant 7

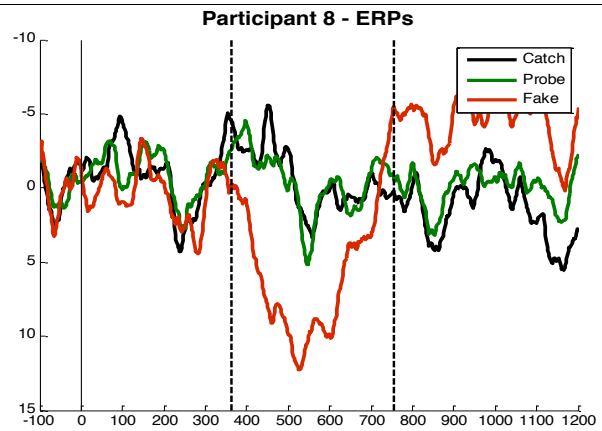

Figure 9 ERP of Participant 8

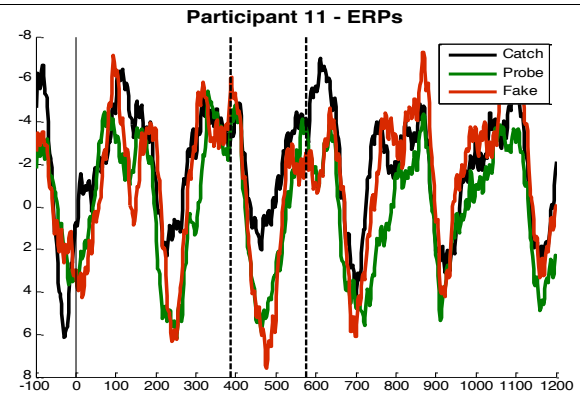

Figure 10 ERP of Participant 11

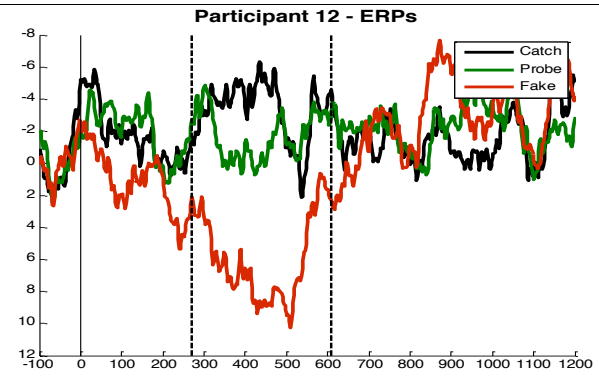

Figure 11 ERP of Participant 12

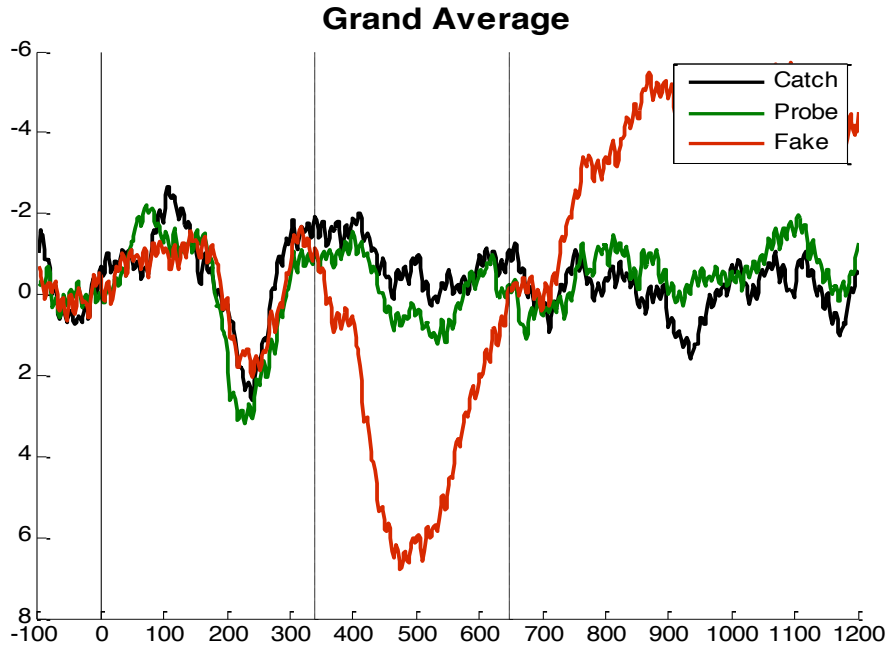

Figure 12 The grand average shows that the *Catch* signal and the *Probe* signal are different between 340ms to 600ms. The *Fake* signal has a large positive peak between 350ms to 650ms.

1.8 P300 Analysis

In the *lie detector* experiment, a participant is considered ***guilty*** when there is a significant difference between the P300 pattern generated from *Probe* trials and the one generated from *Catch* trials. We compare the *Probe* pattern against the *Catch* pattern due to the fact that there is no P300 expected to be generated from *Catch* trials as there is nothing (only irrelevant birthdays) to stimulate a participant's brain during their presentation.

As can be seen from the ERP plots, there was no significant difference between the brain response to real birthdays (*Probe*) and irrelevant birthdays (*Catches*) for most of the participants except some participants who showed the guilty pattern such as participants 6, 7, and 11; see figures 8, 9, and 11. Other participants did not show that pattern clearly such as partcipants 1, 2, 3 ,4 5, 8, 12; see figures 2, 3, 4, 5, 6, 9, and 11 respectively. Thus, in order to invesitigate the difference between the two patterns more closely, some analysis techniques are used in the next sections. In order to determine a participant's null hypothesis distribution, a randomisation procedure was applied [24].

2 DATA ANLAYSES

2.1 Fixed Effects

The standard method used for each participant was defined using the difference between *Probe* and *Catch* conditions in the P300 time window. First, a P300 time window from the grand average *Fake* condition was identified. Note that the inferential logic of our analysis for this method is to characterise a grand average's P300 on the basis of *Fake* trials, where the largest P300s can be expected. Second, for each participant a difference in µV (*Probe– Catch*) was determined for each time point in the (identified) P300 time window. Third, the sum of these differences was determined. A one-sample *t-test* then was calculated on the assumption that the sums of the differences are random samples from a normal distribution with mean 0 and unknown variance.

2.2 Weighted Kernel

2.2.1 Fixed Effects

The kernel of each participant was calculated based on the difference between the grand average of *Fake* and *Catch* waveforms. The process as follows:

1. A P300 time window from the grand average *Fake* condition was identified.
2. From the Grand Average *Fake* and *Catch* conditions, a difference in µV (*Fake – Catch*) was calculated.
3. The total of the *absolute* values obtained in step 2 was calculated.
4. Each difference determined in 2 was divided by the sum calculated in 3.

Let n be the number of time points within the P300 time interval. Also, let $\boldsymbol{w}$ be the weight vector, ***GA_FAKE*** is the grand average of Fake signal, the ***GA_Catch*** is the grand average of Catch signal, and $\boldsymbol{v}$ the vector across

time points for the desired comparison. The weighted kernel can be defined as:

$$\boldsymbol{Shape}(i) = \frac{GA\_\boldsymbol{fake}(i) - GA\_\boldsymbol{catch}i)}{\sum_{j=1}^{n} |GA\_\boldsymbol{fake}(j) - GA\_\boldsymbol{catch}(j)|}$$

The difference between *Probe* and *Catch* is defined as:

$$\boldsymbol{vector}(i) = \big(\boldsymbol{probe}(i) - \boldsymbol{catch}(i)\big) * \boldsymbol{shape}(i)$$

The final *Probe* – *Catch* difference value is defined as $\sum_{i=0}^{n} \boldsymbol{vector}(i)$. For more explanations with examples about the Weighted kernel see figures 13,14, and 15.

2.2.2 Random Effects

The random effects analysis works similarly to the fixed effects analysis except in the method of calculating the weight vector. In random effects analysis, instead of calculating the difference between the grand average *Fake* and *Catch* conditions, the kernel vector was calculated using the difference between the *Fake* and *Catch* waveforms for each participant (individual level) in the P300 time window. Note, in random effects analysis, a P300 time window was identified from a participant's *Fake*.

2.2.3 Flexible templates

The flexible template method works in almost the same way as the random effects template. The reason for applying this method is to resolve a situation in which the *Probe* pattern might be generated earlier or later than the *Fake* pattern. The procedure works as follows:

1- Calculate the weight vector ***W(i)*** in the same way as it was calculated in the weighted Kernel-random effects analysis. Once the weight vector has been defined *W(i),* the length *L* of this vector is determined.

2- Starting from 200 ms from target onset, the *L* time window is determined.

3- Calculate the difference between *Probe* and *Catch* for each time point in the determined window; then apply the difference to the vector weight ***W(i)*** *as* :

$$\boldsymbol{v}(i) = \big(\boldsymbol{probe}(i) - \boldsymbol{catch}(i)\big) * \boldsymbol{w}(i)$$

4- Calculate the weighted difference value as $\sum_{i=0}^{n} \boldsymbol{v}(i)$. If this value is the largest value found so far, store the value as the weighted difference value for a desired participant.

5- The window then moves forward by 1 time point; then it repeats steps 3 and 4 until the start of the L time window reaches 800ms.
The value remaining in store is the flexible template result.

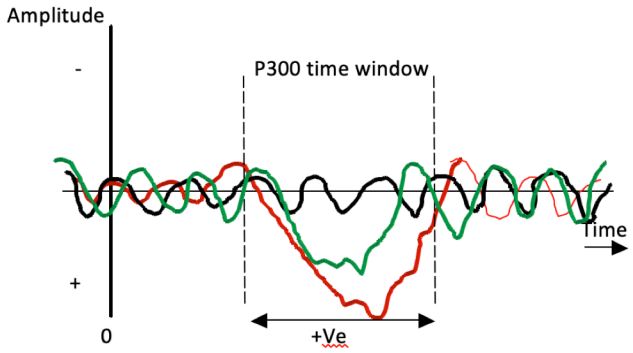

Figure 13 shows that the result of the standard method will be a positive value because the Probe pattern is more positive than the Catch pattern within the P300 time window, in the weight template method will be also positive because both Fake and Probe patterns are in the expected direction (they are pothe positive). Thus, in this example , either of both analysis would work well.

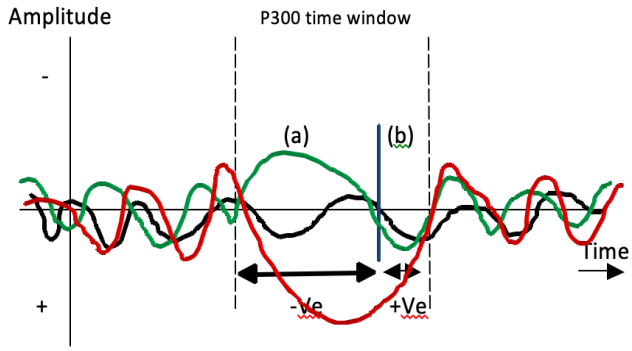

Figure 14 shows that the result of the weight template will be negative value within the time window of (a) because both Fake and Probe patterns are in an opposite directions, while within the time window of(b) the weight template will be positive because both patterns are positive. Whereas, the value of the standard method will be negative because the Probe patterns at the most of the P300 time window is more negative than the Catch pattern.

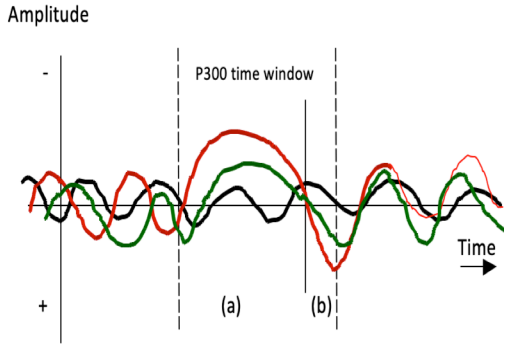

Figure 15 shows that both Fake and Probe conditions within the P300 time window have 'atypical' shape because they are both negative at the most of the P300 time window. However, in this case, the result of the standard method will be a negative value, whereas, in the weight template method within both time window (a) and (b) the result will be a positive value because both conditions Fake and Probe are matching each other each other (they have the same direction at both time windows a and b).

3 RESULTS

3.1 The Standard Method- fixed effects

3.1.1 Group level (t-test)

Participants	Sum of differences between *Probe* and *Catch* ERPs in the P300 interval	Participants	um of differences between *Probe* and *Catch* ERPs in the P300 interval
Participant 1	-11.83426	Participant 7	447.8689
Participant 2	-157.6101	Participant 8	101.7615
Participant 3	-133.4536	Participant 9	-8.1498
Participant 4	-257.8004	Participant 10	87.67007
Participant 5	-127.1255	Participant 11	378.6469
Participant 6	618.9469	Participant 12	288.9241
One sample T-Test			
P Value	ci	df	sd
0.2230	-72.043 to 276 276.683	11	272.0598

Table 1 shows Results of the standard method analysis with fixed effects. It shows the differences between *Catch* and *Probe* patterns that were obtained from the standard method analysis and the results of the one sample t-test.

3.1.2 Individual Level (randomisation)

Participants	P-value from Randomised null hyp. distributions	Participants	P-value from Randomised null hyp. distributions
Participant 1	0.5160	Participant 7	0.0270
Participant 2	0.6960	Participant 8	0.4100
Participant 3	0.6510	Participant 9	0.4770
Participant 4	0.8220	Participant 10	0.3900
Participant 5	0.6340	Participant 11	0.0900
Participant 6	0.0220	Participant 12	0.1960
Average of p_vlaue: **0.4109**			

Table 2 shows the p-values that were calculated from randomisation and standard method analysis - fixed effects.

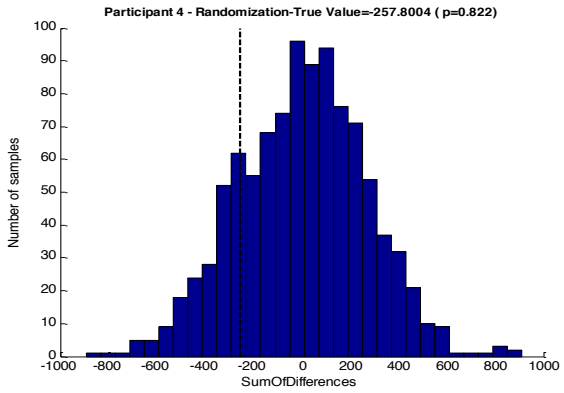

Figure 16 represents the sampling distribution of the standard method calculated from 1,000 randomizations of the *Probe* and *Catch* trials for participant 4. The dashed line in both figures refers to the true observed value (the actual difference between *Probe* and *Catch* ERPs under the standard analysis before the randomization).

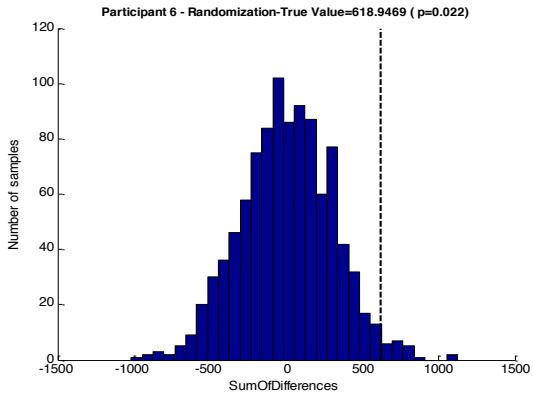

Figure 17 represents the sampling distribution of the standard method calculated from 1,000 randomizations of the *Probe* and *Catch* trials for participant 6. The dashed line refers to the true observed value (the actual difference between *Probe* and *Catch* ERPs under the standard analysis before the randomization.

3.1.3 Discussion

Table 1 shows the results of the standard analysis. As can be seen from the table, only 4 participants (6, 7, 11, and 12) have large positive differences. Participants 4 and 6 have the most negative and positive differences, respectively. From figure (5), it is obvious that it is expected to have a large negative difference due to the fact that the *Catch* pattern within the P300 time window is more positive than *Probe* pattern. In contrast, the *Probe* pattern of participant 6 within the P300 time window is more positive than the *Catch* pattern (see figure 7). Thus, this participant reveals a large difference in the expected direction.

The p-value of the group level analysis that was calculated by using a t-test is 0.2230. It concludes that, in the group level analysis, there is no evidence to reject the null hypothesis, which says that the *Probe* and *Catch* conditions are likely equal. The sampling distributions of the standard method for participants 4 and 6 are shown in figure 16 and figure 17 respectively.

Table 2 shows the results of the individual level analysis, which was based on the randomisation tests. From the table, it can be seen that only 3 participants (6,7, and 11) have small p-values; thus, at the traditional alpha level of alpha = .05, we would only able to reject the null hypothesis twice and conclude that just participants 6 and 7 showed guilty knowledge.

3.2 Weighted Kernel-fixed Effects

3.2.1 Group level (t-test)

Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval	Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval
Participant 1	0.3462	Participant 7	2.9023
Participant 2	-0.8770	Participant 8	0.8494
Participant 3	-1.4744	Participant 9	-0.0860
Participant 4	-0.9248	Participant 10	0.2991
Participant 5	-0.8615	Participant 11	2.7054
Participant 6	3.8233	Participant 12	1.5862
One sample T-Test			
P Value	ci	df	sd
0.1923	-0.4036 to 1.7850	11	1.7223

Table 3 Results of the weighted Kernel analysis with fixed effects. It shows the weighted differences that were obtained from the weighted Kernel-fixed effects analysis and show the results of the t-test the group level analysis.

3.2.2 Individual Level (randomisation)

Participants	P-value from Randomised null hyp. distributions	Participants	P-value from Randomised null hyp. distributions
Participant 1	0.4310	Participant 7	0.0290
Participant 2	0.6680	Participant 8	0.3650
Participant 3	0.7600	Participant 9	0.5250
Participant 4	0.6920	Participant 10	0.4590
Participant 5	0.6710	Participant 11	0.0430
Participant 6	0.0210	Participant 12	0.1990
Average of p_vlaue: **0.4053**			

Table 4 shows the p-values that were calculated from randomisation and weighted Kernel - fixed effects analysis.

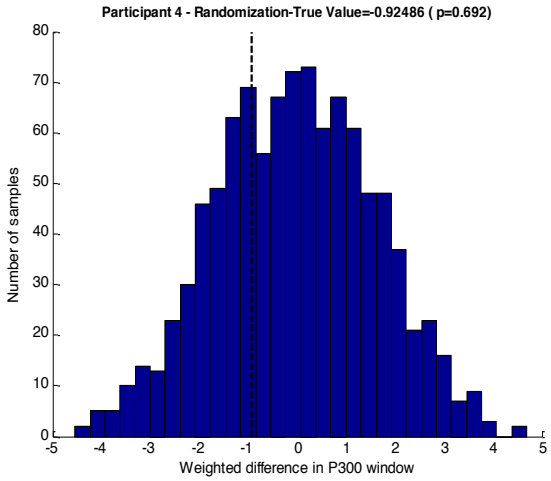

Figure 18 represents the sampling distribution of the weighted Kernel-fixed effects method calculated from 1,000 randomizations of the *Probe* and *Catch* trials for participant 4. The dashed line in the two figures refers to the true observed value (the actual weighted difference between *Probe* and *Catch* ERPs before the randomisation).

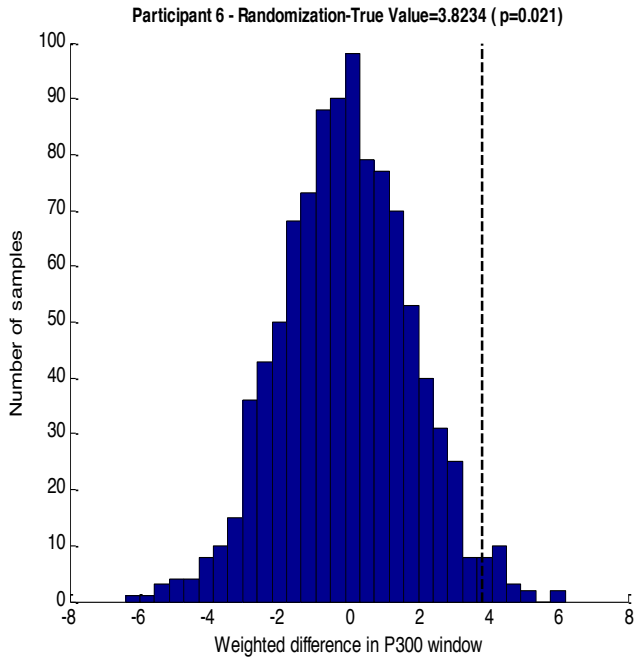

Figure 19 represents the sampling distribution of the weighted Kernel-fixed effects method calculated from 1,000 randomizations of the *Probe* and *Catch* trials for participant 6. The dashed line in the two figures refers to the true observed value (the actual weighted difference between *Probe* and *Catch* ERPs before the randomisation).

3.2.3 Discussion

Table 3 shows the results of the weighted Kernel-fixed effects analysis. Only 7 participants have positive weighted differences. Participant 6 has the largest positive weighted difference due to the large difference between *Probe* and *Catch* patterns and, at the same time, the large difference between *Fake* and *Catch* patterns (see figure 7), which have the same shape through time. As stated earlier, in this analysis, when the difference between *Probe* and *Catch* patterns matches the difference between *Fake* and *Catch* patterns, the weighted difference is expected to be large. In contrast, participant 3 has the most negative weighted difference. From the participant ERP in figure 5, within the P300 time window, the *Probe* pattern is mostly either smaller or equal to the *Catch* pattern, while the *Fake* exhibits a classic (positive) pattern relative to the *Catch*. This caused the difference (*Probe*-*Catch*) to be a negative value when template weighted.

The P-value that was obtained from the group level analysis was 0.1923. That suggests that, under the group level analysis, there is still not enough evidence to reject the null hypothesis, which states that *Probe* and *Catch* patterns are statistically equal.

Table 4 contains the p-values that were obtained from the randomisation test. Participants 3 and 6 have the largest (0.7600) and the smallest (0.0210) p-values, respectively.

This is owing to the fact that participants 3 and 6 have the smallest and largest true observed values, respectively (see table 3). In general, at the significant level of alpha = .05, participants 6 ,7, and 11 showed the guilty pattern. The sampling distribution of the weighted Kernel-fixed effects method are shown in figure 18 and 19 respectively.

3.3 Weighted Kernel-Random Effects

3.3.1 Group level (t-test)

Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval	Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval
Participant 1	1.6262	Participant 7	3.2662
Participant 2	1.1016	Participant 8	0.7372
Participant 3	-1.0004	Participant 9	0.1152
Participant 4	1.2964	Participant 10	0.4058
Participant 5	0.8945	Participant 11	3.1301
Participant 6	2.7341	Participant 12	2.3343
One sample T-Test			
P Value	ci	df	sd
0.0034	0.5656 to 2.2079	11	1.2924

Table 5 Results of the weighted Kernel analysis with random effects. (a) shows the weighted differences that were obtained from the weighted Kernel-random effects analysis. (b) shows the results of the group level t-test.

3.3.2 Individual Level (Randomisation)

Participants	P-value from Randomised null hyp. distributions	Participants	P-value from Randomised null hyp. distributions
Participant 1	0.1190	Participant 7	0.0240
Participant 2	0.1560	Participant 8	0.3510
Participant 3	0.6830	Participant 9	0.4540
Participant 4	0.0560	Participant 10	0.4010
Participant 5	0.3490	Participant 11	0.0170
Participant 6	0.0090	Participant 12	0.1050

Table 6 shows the p-values that were calculated from randomisation and weighted Kernel - random effects.

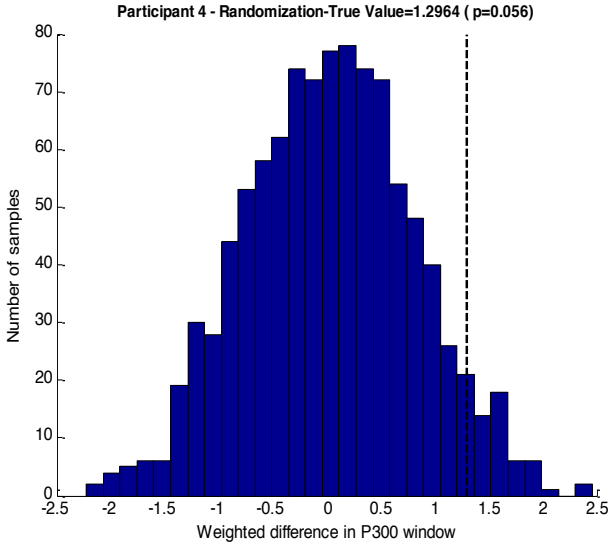

Figure 20 represents the sampling distribution of the weighted Kernel-random effects analysis calculated from 1,000 randomisations of the *Probe* and *Catch* trials for participant 4. The dashed line in both figures refers to the true observed value (the actual weighted difference between *Probe* and *Catch* ERPs under the weighted Kernel-random effects analysis before the randomisation).

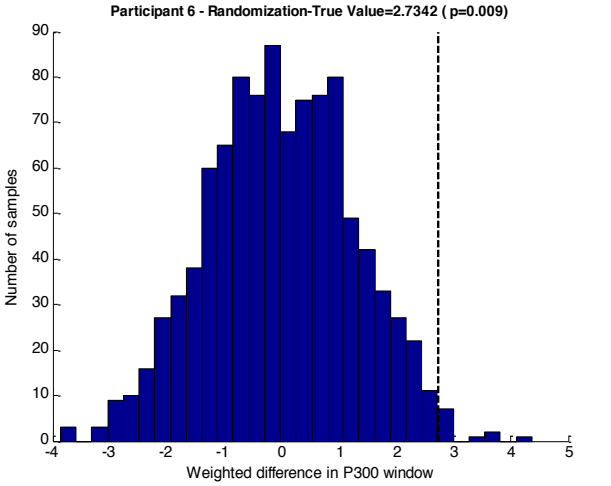

Figure 21 represents the sampling distribution of the weighted Kernel-random effects analysis calculated from 1,000 randomisations of the *Probe* and *Catch* trials for participant 6. The dashed line refers to the true observed value (the actual weighted difference between *Probe* and *Catch* ERPs under the weighted Kernel-random effects analysis before the randomisation).

3.3.3 Discussion

Table 5 shows the results of the weighted Kernel –random effects analysis. In contrast to the previous analysis, it is worth noting that, in the random effects analysis, the

weighted Kernel was based on the individual's *Fake* ERP; the P300 interval was also defined from the individual's *Fake* ERP. The table reveals that participants 6, 7, 11 and 12 have large weighted differences in the expected direction. By looking to their ERPs in figures 7, 8, 10, and 11, it can be seen that there is a reasonable difference between the *Probe* and *Catch* pattern within the P300 time window that is well matched to the *Fake-Catch* pattern. Actually, compared to the previous analysis (weighted Kernel- fixed effects), in this analysis, there are dramatic changes in the weighted difference values with most of the participants. In the previous analysis, the weighted differences for participant 2, 4, 5, and 9 were negative values, while in this analysis, there is only one negative weighted difference involving participant 3. In fact, by looking at participant 3's ERPs in figure 4, it can be seen that the *Probe* pattern within the P300 time window is either smaller or equal to the *Catch* pattern. At the same time, there is a large posistive difference between *Fake* and *Catch* patterns. Thus, from the weighted template equations, the weighted difference is expected to be a negative value.

The p-value that was obtained from the group level analysis was 0.0034. It suggests that, under the group level analysis, there is strong evidence for a difference between *Probe* and *Catch* patterns.

Table 6 contains the p-values that were generated from the randomisation test. In fact, there are significant changes in p-values compared to the those that were obtained from the weighted Kernel-fixed effects. For instance, with the weighted Kernel-fixed effect analysis, the p-value of participant 2 was 0.6680, whereas, in this analysis. it dropped dramatically to 0.1560. This change is due to the fact that the fixed analysis was based on calculating the difference between *Fake* and *Catch* patterns from the Grand Average of both conditions. By looking at the Grand Average ERPs in figure 12, it is clear that there is a large positive difference between *Fake* and *Catch* patterns. At the same time, the difference between the *Probe* and *Catch* patterns of the participant is expected to be negative because the *Probe* pattern is negative from 320 to 500ms (see figure 5). Thus, from the weighted Kernel fixed effects procedure, the weighted difference value is expected to be a negative value and, therefore, the p-value was large (p-value=0.6830).

In contrast, the weighted template random effects were based on the individual ERPs. In figure 3, from participant 2's ERPs, it can be seen that, at the time between 360ms to 500ms, the *Catch* pattern is more positive than both conditions, the *Probe* and *Fake* patterns, and from 500ms to the end of the P300 time window the difference between *Fake* and *Catch* mostly matches the difference between *Probe* and *Catch* patterns. This is what made the weighted difference of participant 2 positive (=1.1016) in this analysis. In other words, in the weighted Kernel-fixed effects, the large difference between *Fake* and *Catch* patterns that was derived from the Grand Average might affect the weighted difference value so that it becomes a negative value, especially when the *Probe* pattern is more negative than the *Catch* pattern within the P300 interval. The random effects analysis was based on the difference between individual *Fake* and *Catch* patterns. This difference was not large in reference to some participants, such as participant 2. Thus, most of the weighted differences were positive values with weighted Kernel-random effects.

Another aspect which might make the random effects analysis powerful is that it is based on the P300 time window of the individual's *Fake* condition, unlike in the fixed effect analysis, which was based on the P300 time window of the Grand Average of the *Fake* condition. This actually might cause changes to the p-values of some participants, such as participant 4. By looking at participant 4's ERPs in figure 8, it can be seen that the P300 time window started 100 ms later and ended 100 ms later when compared to the P300 time window of the Grand Average (see figure 12). Thus, the p-value for participant 4 was 0.6920 in the weighted Kernel-fixed effects and was 0.0560 in the random effects analysis. However, the individual level average p-values gets better comparing to the previous analyses. In general, at the significant level of alpha = .05, participants 4, 6, 7, and 11 showed the guilty pattern. The sampling distribution of the weighted Kernel-random effects analysis for participant 4 and 6 are shown in figure 20 and 21 respectively.

3.4 Weighted Kernel - Flexible Template

3.4.1 Group Level (t-test)

Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval	Participants	Weighted Difference between *Probe* and *Catch* ERPs in the P300 interval
Participant 1	1.3490	Participant 7	3.7678
Participant 2	0.2974	Participant 8	0.6769
Participant 3	-0.4790	Participant 9	-0.1725
Participant 4	1.8830	Participant 10	0.6323
Participant 5	0.4758	Participant 11	2.3015
Participant 6	2.1571	Participant 12	2.1168
One sample T-Test			
P Value	ci	df	sd
0.0048	0.4680 to 2.0325	**11**	**1.2924**

Table 7 Results of the flexible weighted Kernel analysis.

Participants	P-value from Randomised null hyp. distributions	Participants	P-value from Randomised null hyp. distributions
Participant 1	0.1730	Participant 7	0.0080
Participant 2	0.3870	Participant 8	0.3810
Participant 3	0.5740	Participant 9	0.5500
Participant 4	0.0030	Participant 10	0.3910
Participant 5	0.4250	Participant 11	0.1100
Participant 6	0.0410	Participant 12	0.1450
Average of p_vlaue: **0. 0.2657**			

Table 8 shows the p-values that were calculated from randomisation and the flexible weighted Kernel analysis.

3.4.2 Final Discussion

Table 7 shows the results of the flexible weighted Kernel. As stated earlier, this analysis works similarly to the weighted Kernel-random effects analysis except that it was based on the weighted difference between *Probe* and *Catch* patterns arising from the best template position. Actually, compared to the previous analysis, there were some changes involving some participants, such as participant 4. The p-value of participant 4 was 0.0560 in the weighted Kernel random effects analysis, whereas in the flexible template analysis, the p-value was 0.003. The reason for this is that the *Probe* pattern might be generated later or earlier than the *Fake* pattern. The p-value that was obtained from the group level analysis was 0.0048. That suggests that, under the group level analysis, there is a significant difference between *Probe* and *Catch* patterns. However, there are doubts about the accuracy of the way this analysis was implemented due to the fact that in the group level analysis, the null hypothesis of the t-test was that the mean is equal to 0 (i.e., there is no difference between *Probe* and *Catch* patterns), but this analysis, in fact, was based on applying the template to the time window that contains the *best* difference between *Probe* and *Catch* pattern,which in all but trivial situations will be bigger than zero, even when the null hypothesis is true. Thus, comparing the weighted difference to zero might be an inappropriate test.

4 CONCLUSION

In previous sections of this research project, different analytical approaches were used to classify EEG data. The EEG data was recorded during a *lie detector* experiment. As stated earlier, the logic of the experiment is that a participant is considered guilty when the pattern obtained for his or her real birthday (*Probe*) significantly differs from the pattern for irrelevant birthdays (*Catches*). Thus, this preliminary analysis focused on finding an appropriate analysis method that could classify *Probe* and *Catch* patterns with high accuracy.

A comparison between the analysis methods was conducted on both group and individual levels. For group level analysis, one sample t-tests were applied, and the null hypothesis H_0 was that the differences (with the standard method) or the weighted differences (with the template method) between *Probe* and *Catch* patterns are random samples from a normal distribution with a mean =0. For the individual level analysis, a null hypothesis distribution of each participant was created by using a randomisation test.

On the group level analysis, the p-values for the standard method, weighted Kernel-fixed effects, and weighted Kernel-random effects analyses were 0.2230, 0.1923, and 0.0034, respectively. On the individual level, for each analysis method, averages of the individual's p-values were calculated. The average p-value for the standard method, weighted Kernel-fixed effect, weighted Kernel-random effects, and flexible weighted Kernel were 0.4109, 0.4053, 0.2270, and 0.2657, respectively.

From these results, it can be concluded that the weighted Kernel-random effects classifier outperforms the other analysis methods: in the random effects analysis, the weighted Kernel was determined based on participants' *Fake* and *Catch* patterns, whereas in the fixed effects analysis, the template was defined based on the Grand Average *Fake* and *Catch* patterns.

The favoured aspect of the standard analysis was that it is simple to use when there is a noticeable difference between ERPs such as the difference between *Fake* and *Catch* patterns in this study. However, in this work, it cannot be used to determine whether the *Probe* has a true P300 component by comparing it to the *Catch* pattern because in some situations, the shape of the P300 signal is atypical, which might affect the accuracy of the analysis.

The weighted Kernel-fixed effects were used to resolve the matter of the P300 signal shape. However, the analysis results were, in some ways, the same as the results of the standard method. This was due to the fact that the fixed effects analysis was based on the Grand Average *Fake* patterns and on the P300 interval of the Grand Average. Actually, this affected the analysis results, as was discussed earlier in this paper in reference to participants 2 and 4.

The weighted Kernel-random effects were used as an alternative to using the Grand Average. It was based on the individual's pattern and on the individual's *Fake* P300 time window. The results that were discussed earlier may reveal some important differences between *Probe* and *Catch* patterns, especially in reference to participant 4 (see

the discussions of the weighted Kernel-random effects analysis).

The flexible weighted Kernel was implemented to treat the situation when the *Probe* P300 interval of a participant was generated earlier or later than the *Fake* P300 interval. Despite the fact that the results of the flexible template analysis were mostly similar to the weighted Kernel-random effects analysis, in the group level analysis, comparing our null hypothesis to 0 might be inappropriate. Thus, more research on this analysis is needed.

From these findings it can be concluded that the weighted Kernel-random effects provide a more appropriate analysis that can be used to investigate the differences between *Probe* and *Catch* patterns in this work due to the fact that it can classify individual ERP patterns in regard to the shapes and the time window of the P300 component.

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