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A survey of the dummy face and human face stimuli used in BCI paradigm

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HIGHLIGHTS

- Dummy face stimulus was easy to be edited and had no copyright infringement problems when it was applied to BCI system.
- There was no significant difference in the latency and amplitude of ERPs between the dummy face and the human face stimulus.
- Dummy face pattern obtained as high classification accuracy and information transfer rate as the human face pattern, which would be a good choice for optimizing the stimulus of BCI system.

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ABSTRACT

Background: It was proved that the human face stimulus were superior to the flash only stimulus in BCI system. However, human face stimulus may lead to copyright infringement problems and was hard to be edited according to the requirement of the BCI study. Recently, it was reported that facial expression changes could be done by changing a curve in a dummy face which could obtain good performance when it was applied to visual-based P300 BCI systems.
New method: In this paper, four different paradigms were presented, which were called dummy face pattern, human face pattern, inverted dummy face pattern and inverted human face pattern, to evaluate the performance of the dummy faces stimuli compared with the human faces stimuli.
Comparison with existing method(s): The key point that determined the value of dummy faces in BCI systems were whether dummy faces stimuli could obtain as good performance as human faces stimuli. Online and offline results of four different paradigms would have been obtained and comparatively analyzed.
Results: Online and offline results showed that there was no significant difference among dummy faces and human faces in ERPs, classification accuracy and information transfer rate when they were applied in BCI systems.
Conclusions: Dummy faces stimuli could evoke large ERPs and obtain as high classification accuracy and information transfer rate as the human faces stimuli. Since dummy faces were easy to be edited and had no copyright infringement problems, it would be a good choice for optimizing the stimuli of BCI systems.

1. Introduction

A brain-computer interface (BCI) allows users to send messages or control the external devices without physical actions, and provides a new output pathway for the brainthat is different from the conventional neuromuscular pathways of peripheral nerves and muscles (Mak and Wolpaw, 2009; Wolpaw et al., 2002). The brain-computer interface is commonly based on EEG recorded non-invasively via electrodes placed on the surface of the head (Allison et al., 2007). While a variety of mental tasks have been explored for BCI control, most BCI systems rely on motor imagery or visual evoked potentials (Allison et al., 2007, 2008; Birbaumer and Cohen, 2007; Daly et al., 2013; Jin et al., 2014; Kübler et al., 2001; Mak and Wolpaw, 2009; Ortner et al., 2011; Wolpaw et al., 2002; Wang et al., 2014).

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A P300 BCI is a typical example of many different BCI systems which are based on visual, audio or tactile stimuli (Fazel-Rezai, 2007; Hill et al., 2004; Jin et al., 2014; Kaufmann et al., 2014; Kim et al., 2011; Mak et al., 2011). P300 is elicited by the events that subjects consider importantly (Acqualagna and Blankertz, 2013; Farwell and Donchin, 1988; Polich, 2007). The P300 BCI was first applied to speller, in which a 6×6 stimuli matrix was used (Farwell and Donchin, 1988). Presently, the P300 BCIs have been tested not only on healthy users, but also on patients (Allison et al., 2008; Fazel-Rezai, 2007; Kaufmann et al., 2014; Kübler et al., 2001).

Although many P300 BCI systems had been developed, they were still in the laboratory stage because of the low speed and unstable accuracy for different subjects. In order to improve the performance of P300 BCIs, many studies were focused on the signal processing and pattern recognition methods to increase the classification accuracy of P300 BCIs (Aloise et al., 2011; Blankertz et al., 2011; Brunner et al., 2010; Cichocki et al., 2008; Emily et al., 2010; Hoffmann et al., 2008; Lotte et al., 2007; Mugler et al., 2008; Speier et al., 2013; Xu et al., 2004). Optimized paradigms to evoke event related potentials (ERPs) were designed to expand the applicability for Amyotrophic Lateral Sclerosis (ALS) sufferers and Spinal Cord Injury patients (Liu et al., 2010; Rohm et al., 2013; Treder et al., 2011). The stimuli configuration was optimized to improve the reliability of the P300 speller systems (Jin et al., 2011; Townsend et al., 2010). The goal of these studies was to increase the differences between attended events and ignored events and to classify the target and non-target trials correctly.

Some studies adopted new stimuli paradigms to enhance other components of the ERPs that occurred before or after the P300. P300 BCIs typically depended on not only the P300, but also other visual ERPs such as the N100, N200, and N400 components (Allison and Pineda, 2003; Jin et al., 2010; Kaufmann et al., 2011; Sellers and Donchin, 2006; Treder and Blankertz, 2010). Guo et al. (2008) introduced a novel way to propose visual evoked potentials in a BCI: the stimuli just moved, instead of flashed, to evoke a motion-onset visual evoked potential (M-VEP). They stated that this stimuli paradigm might offer good performance to a conventional P300 BCI (Guo et al., 2008; Hong et al., 2009; Pires et al., 2011). Jin et al. combined the P300 and M-VEP by moving flash stimulus to improve a P300 BCI system (Jin et al., 2012a). Kaufmann et al. (2011) introduced stimuli that were transparently overlaid with famous faces to increase the classification accuracy by evoking a large N400 (Kaufmann et al., 2011, 2012). Zhang et al. (2012) reported that N170 and vertex positive potentials (VPP) also improved the classification accuracy of P300 BCIs with stimuli that changed to faces (Zhang et al., 2012). However, while these researches succeeded in improving the reliability of identifying target flashes (Liu et al., 2010; Townsend et al., 2012), there was another method that could further increase the ERP-based BCIs. Some studies were focused on decreasing the interference by reducing the number of adjacent flashes (Frye et al., 2011; Liu et al., 2010; Townsend et al., 2010). But increasing the number of flashes of each trial would reduce the speed of the BCI systems. If the false evoked ERPs in non-target flashes caused by the interference of spatially adjacent stimuli and fatigue experienced by users could both be decreased, the classification accuracy of ERPs and usability of BCIs could both be increased. Jin et al. presented a paradigm based on the expression changes of dummy face. This facial expression change pattern was designed to reduce the interference, the annoyance and the fatigue experienced by users without decreasing the speed of the BCI systems (Jin et al., 2014). However, only dummy face was used in that study. It was proven that the use of a face pattern was superior to a flash pattern (Jin et al., 2012b). There was no study that showed the difference between dummy faces and human faces that were used in BCI systems.

In this paper, the primary goal of this study was to survey the difference between the dummy faces stimuli and the human faces stimuli used in BCI paradigms on ERPs, classification accuracy and information transfer rate. Four different paradigms were presented which were called dummy face pattern, human face pattern, inverted dummy face pattern and inverted human face pattern. All faces were monochromatic, so it could eliminate the interference of colors. We supposed that there were no significant differences between the human faces pattern and the dummy faces pattern. If dummy faces stimuli could obtain as good performance as the human faces stimuli, there would be two advantages of using the dummy face in BCI systems compared with the human faces stimuli. First, dummy face would not have copyright infringement problems; second, dummy face was easy to be edited. Jin et al. (2014) reported that the facial expression changes could be realized by changing a curve in a dummy face (Jin et al., 2014).

2. Materials and methods

2.1. Subjects

Ten healthy subjects (8 males, aged 21–25 years, mean 23.5 ± 1.35) participated in this study. All subjects signed a written consent form prior to this experiment and were paid for their participation. The local ethics committee approved the consent form and experimental procedure before any subjects participated. All subjects' native language was Mandarin Chinese. Five subjects had used P300 BCI before this study.

2.2. Stimuli and procedure

After being prepared for EEG recording, the subjects were seated in a comfortable chair 70 ± 5 cm from a standard 24 in. LED monitor (60 Hz refresh rate, 1920×1080 screen resolution) in a shielded room. The stimuli were presented in the middle of the screen. During data acquisition, subjects were asked to relax and avoid unnecessary movement. Fig. 1 shows the display presented to all subjects. It is a hexagon with six small circles at each of the six corners. The distance between two adjacent circles' center points is 4 cm (visual angle 3.8°), the distance between the center point of the hexagon and the center point of the circle is 4 cm (visual angle 3.8°) and the radius of the small circle is 1 cm (visual angle 0.95°). There were four conditions in this study, which differed only in the stimuli images.

The dummy face pattern proposed in this study consists of as simple lines drawing of a 'happy face' which is the target stimulus. The drawing includes two eyes with eyebrows and a mouth, each of which is represented by simple arcs and circle drawn in monochrome. All line is black. The stimulus on time is 200 ms, and off time is 100 ms. The inverted dummy face condition contains all the same elements as the dummy face condition (the same arcs and circles), but dummy face is inverted. The human face pattern is a monochrome photo which a man has a happy smile. This photo is processed like the dummy face. They all have the same size and brightness. Finally, the inverted human face pattern used the same image as the human face pattern, but the flash picture is inverted. The stimulus on and off time were same as the dummy face pattern.

The four conditions changed the stimuli in the red box of Fig. 1. The red box was not shown in the real interface. The stimuli off state (background state) can be seen in the left column of Fig. 1 and the stimuli on state can be seen in the right column of Fig. 1.

The term 'flash' throughout this paper was used to refer to each individual event. In each trial of each condition, each circle was changed once. Therefore, a single character flash pattern was used here (Guger et al., 2009), and the single image changed individually.

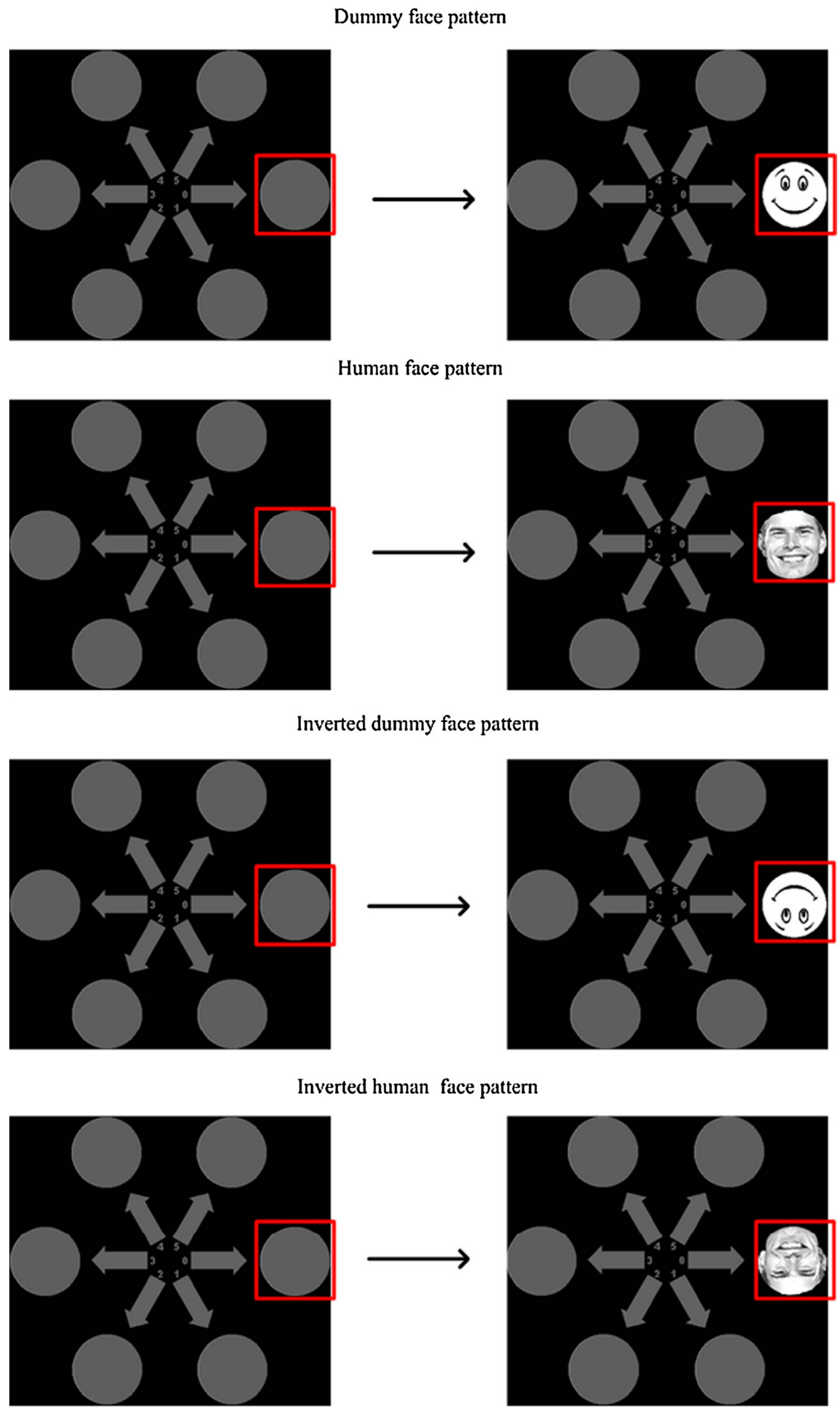

Fig. 1. The display during the online runs. The feedback sequence is presented at the top of the screen.

In order to simplify our issues, we use the term 'flash' throughout this paper to refer to these changes.

2.3. Experiment setup, offline and online protocols

EEG signals were recorded with a g.USBamp and a g.EEGcap (Guger Technologies, Graz, Austria) with a sensitivity of 100 μV, band pass filtered between 0.1 and 30 Hz, and sampled at 256 Hz. We recorded from 14 EEG electrode positions. Based on the extended International 10-20 system (see Fig. 2). The right mastoid electrode was used as the reference and the front electrode (FPz) was used as the ground. Data were recorded and analyzed by using the ECUST BCI platform software package which was developed by East China University of Science and Technology.

Each flash reflected each time a stimulus changed from a background stimulus. One trial (or one sequence) contained all flashes

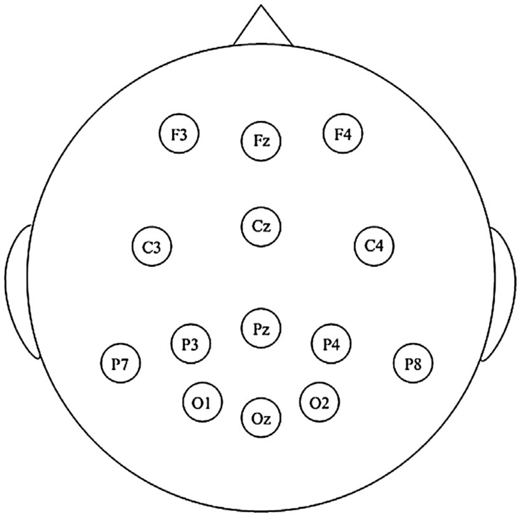

Fig. 2. Configuration of electrode positions.

with each of the six flash patterns. For all patterns had 200 ms flashes followed by a 100 ms delay, each trial lasted 1.8 s. A trial block referred to a group of trials with the same target. During offline testing, there were 16 trials per trial block and each run consisted of five trial blocks, each of which involved a different target. Subjects had a 2 min break after each offline run. During online testing, the number of trials per trial block was two. Subjects attempted to identify 24 targets continuously during online testing (see Fig. 3).

There were four conditions, which were presented to each subject in random order. For each condition, each subject firstly took part in three offline runs. Subjects had 2-min rest between each offline run. After all offline runs of the four patterns, subjects were asked to attempt to identify 24 targets (i.e. 24 trial blocks) continuously for each condition in the online experiment. Feedback and target selection time was 4 s before the beginning of each trial block (counting the 'flashes' in one of the six circles, see Fig. 1). Subjects had 2-min rest before starting the online task for each condition. A white arrow cue was used to show the target (human face or dummy face) which the subjects should focus on and count the flash numbers in both online and offline experiments. The feedback which obtained from an online experiment was shown on the top of the screen. After the BCI system identified the target that the subject focused on, the feedback was shown by using a white block around the target. The white block feedback was shown to subjects. The feedback on the top of the screen was used to record the result of one online experiment.

2.4. Feature extraction procedure

A third-order Butterworth band pass filter was used to filter the EEG between 0.1 and 30 Hz. The EEG was then down-sampled from 256 to 64 Hz by selecting every fourth sample from the filter EEG. The first 800 ms of EEG after presentation of a single stimulus was used to extract the feature from each channel. For the offline data, Windsorizing was used to remove the electrooculogram (EOG). The 10th percentile and the 90th percentile were computed for the samples from each electrode. Amplitude values lying below the 10th percentile or above the 90th percentile were respectively replaced by the 10th percentile or 90th percentile (Hoffmann et al., 2008).

2.5. Classification scheme

Bayesian linear discriminant analysis (BLDA) is an extension of Fisher's linear discriminant analysis (FLDA) that avoids over fitting. The detail of the algorithm can be found in Hoffmann et al. (2008). BLDA was selected because of its demonstrated for its demonstrated classification performance in P300 BCI applications (Hoffmann et al., 2008). Data acquired from offline training were used to train the classifier using BLDA and obtain the classifier model. This model would be used in the online system.

2.6. Raw bit rate

In this paper, we used one bit rate calculation method called raw bit rate (RBT) which was calculated by the formula (1).

$$B = \log_2 N + P\log_2 P + (1-P)\log_2\left[\frac{1-P}{N-1}\right] \quad (1)$$

The P denoted the accuracy. The T was the completion time of the target selection tasks. Bit rate is an objective measure for measuring improvement in a BCI and for comparing different BCIs (Wolpaw

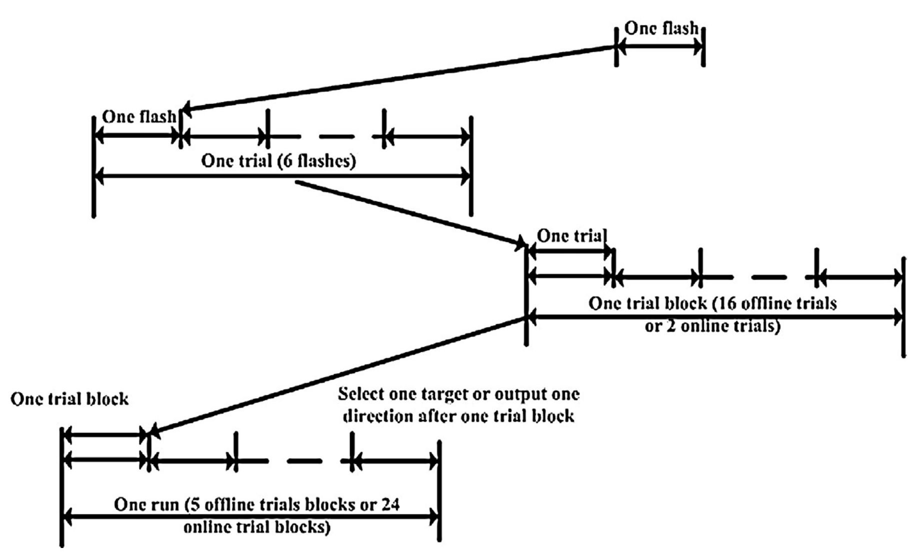

Fig. 3. One run of the experiment for online and offline experiments.

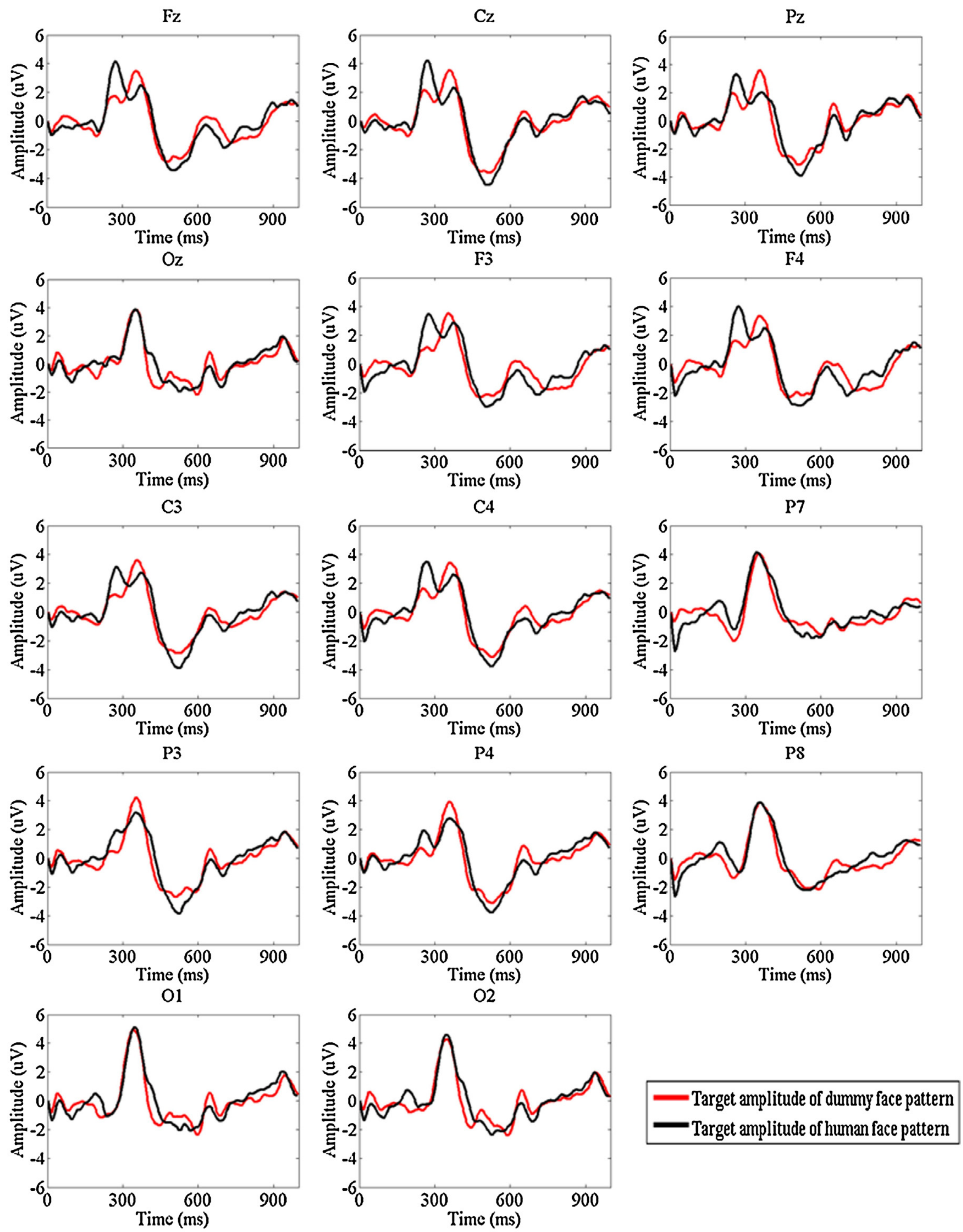

Fig. 4. Grand averaged ERPs of target across subjects 1–10 over 14 electrode sites, including the dummy face pattern and the human face pattern.

et al., 2002). RBT was calculated without selection time and was defined in Wolpaw et al. (2002).

3. Results

In this paper, electrode P7 was selected to show the N200 difference among four patterns, which was commonly chosen for measuring the N200 (Hong et al., 2009); electrode Pz was selected to show the P300 difference among four patterns, which was commonly chosen for measuring the P300; and electrode Fz was selected to show the N400 difference among four patterns, which was commonly chosen for measuring the N400 (Curran and Hancock, 2007). Alpha is 0.05 which is used as statistical significant level for paired samples t-test.

Fig. 4 shows the grand averaged amplitude of target flashes across subjects 1–10 over 14 electrode sites for the dummy face pattern and the human face pattern. Fig. 4 showed that the grand averaged ERPs of the dummy face pattern were similar to the

Table 1
Averaged peak values and averaged latency of N200 at P7, P300 at Pz and N400 at Fz. 'DF-P' denotes the dummy face pattern, 'HF-P' denotes the human face pattern, 'IDF-P' denotes the dummy face pattern and 'IHF-P' denotes the inverted face pattern.

ERP	Electrodes	Amplitude (μV)				Latency (ms)			
		DF-P	HF-P	IDF-P	IHF-P	DF-P	HF-P	IDF-P	IHF-P
N200	P7	−2.7592	−2.6975	−2.5537	−2.5217	251.56	247.27	269.14	246.48
P300	Pz	4.6187	5.1442	4.8911	4.7226	336.33	318.36	316.41	340.54
N400	Fz	−4.9411	−5.3862	−5.7252	−5.8393	575.39	555.86	585.16	548.44

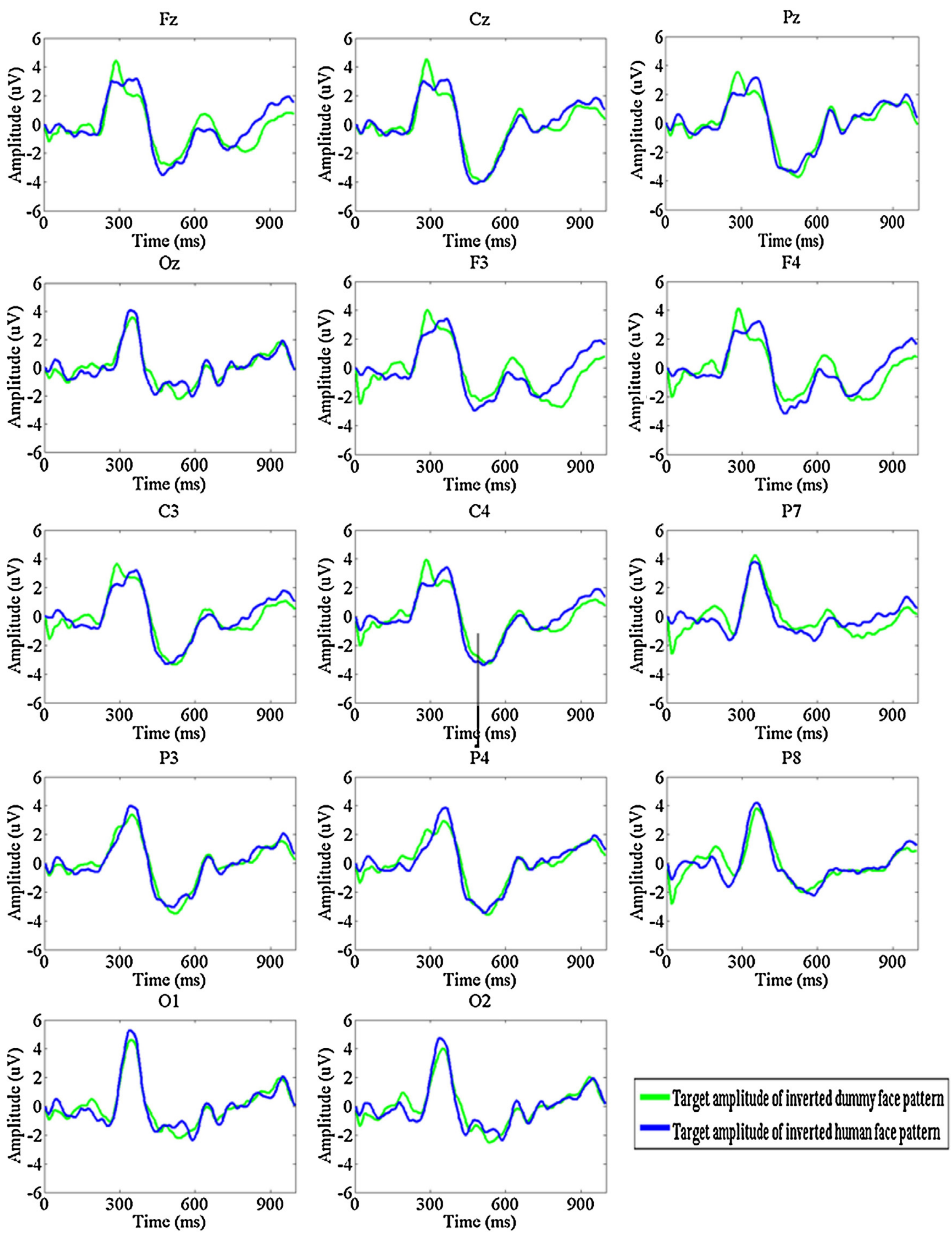

Fig. 5. Grand averaged ERPs of target across subjects 1–10 over 14 electrode sites, including the inverted dummy face pattern and the inverted human face pattern.

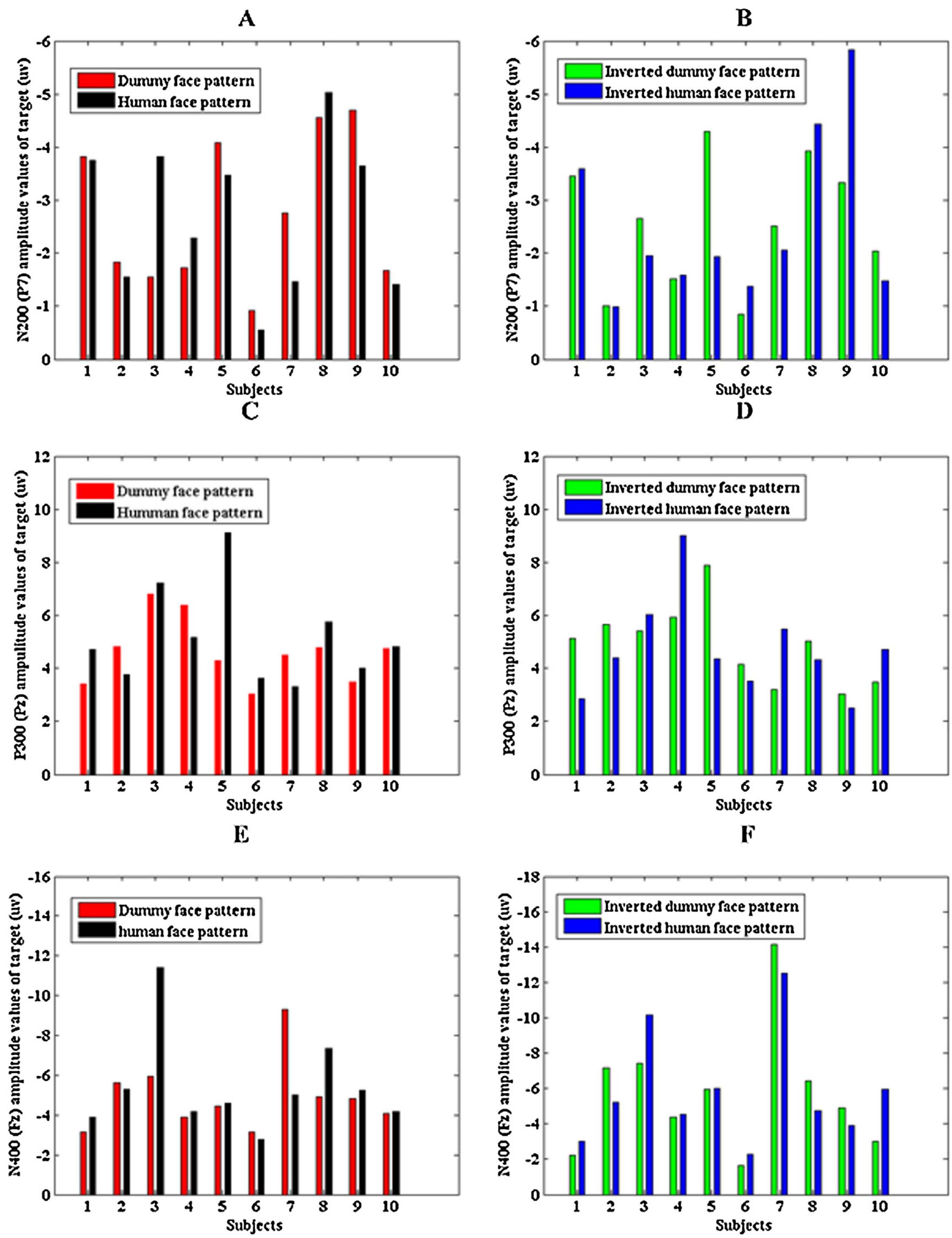

Fig. 6. Peak values of N200 on P7 (panels (A) and (B)), P300 on Pz (panels (C) and (D)) and N400 on Fz (panels (E) and (F)) across 10 subjects. The red represents the peak values of the dummy face pattern; the black represents the peak values of the human face pattern; the green represents the peak values of the inverted dummy face pattern; the blue represents the peak values of the inverted human face pattern. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

human face pattern. We calculated the ERP amplitude correlation of the dummy face pattern and the human face pattern at P7 ($R = 0.8710$, $p < 0.05$), Pz ($R = 0.9119$, $p < 0.05$) and Fz ($R = 0.8842$, $p < 0.05$), which showed high correlation on ERPs between the two patterns. The peak points of N200 at P7, the peak points of P300 at Pz and the peak points of N400 at Fz were calculated for each subject (see Fig. 6A, C and E). A paired samples t-test was used to show the peak points difference between the two patterns. No significant difference was found on N200 ($t = -0.1932$, $p > 0.05$), on P300 ($t = -0.9426$, $p > 0.05$) and on N400 ($t = 0.5796$, $p > 0.05$). The averaged peak values of N200 at P7, P300 at Pz and N400 at Fz for the dummy face pattern and the human face pattern were shown in Table 1.

Fig. 5 shows the grand averaged amplitude of target flashes across subjects 1–10 over 14 electrode sites for the inverted dummy face pattern and the inverted human face pattern. Fig. 5 showed that the grand averaged ERPs of the inverted dummy face were similar to the inverted human pattern. We calculated the ERP

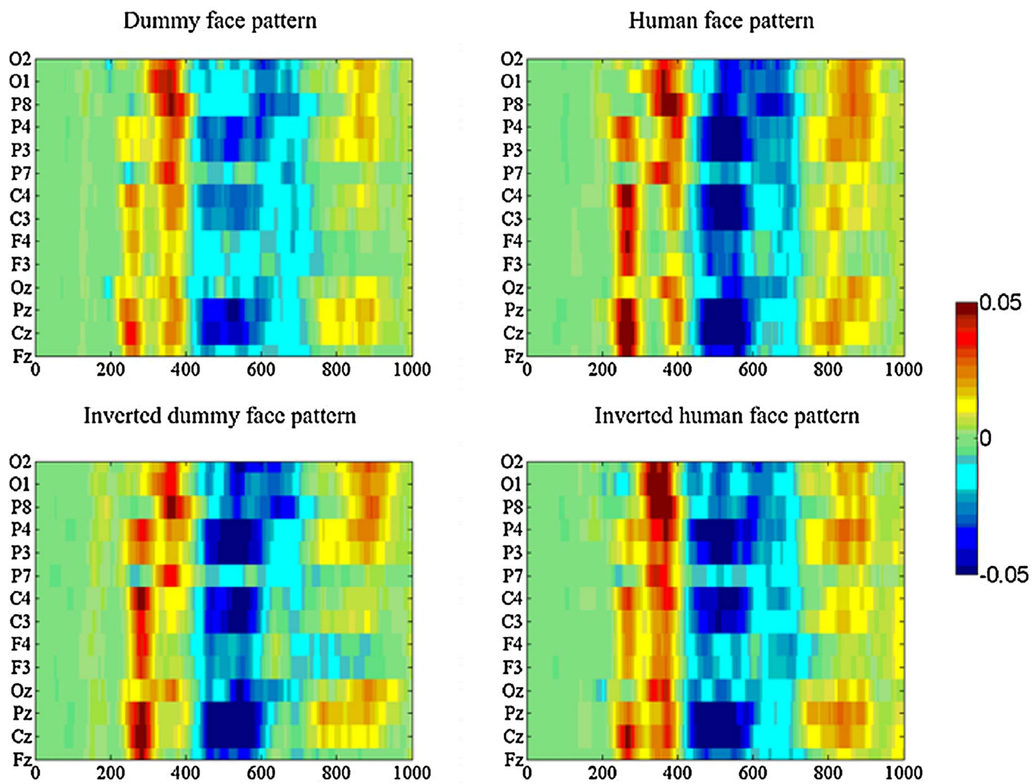

Fig. 7. *R*-squared values of all ERPs. *R*-squared values of ERPs form all paradigms at 0–1000 ms averaged from subject 1 to 10 on sites Fz, Cz, Pz, Oz, F3, F4, C3, C4, P7, P3, P4, P8, O1 and O2.

amplitude correlation of the inverted dummy face pattern and the inverted human face pattern at P7 ($R = 0.8116$, $p < 0.05$), Pz ($R = 0.9545$, $p < 0.05$) and Fz ($R = 0.8991$, $p < 0.05$), which showed high correlation on ERPs between the two patterns. The peak points of N200 at P7, the peak points of P300 at Pz and the peak points of N400 at Fz were calculated for each subject (see Fig. 6B, D and F). A paired samples *t*-test was used to show the peak points difference between the two patterns. No significant difference was found on N200 ($t = -0.0830$, $p > 0.05$), on P300 ($t = 0.2636$, $p > 0.05$) and on N400 ($t = 0.2083$, $p > 0.05$). The averaged peak values of N200 at P7, P300 at Pz and N400 at Fz for the inverted dummy face pattern and the inverted human face pattern were shown in Table 1.

Fig. 7 shows the averaged *R*-squared values of ERPs of all conditions. A paired samples *t*-test was used to show the *R*-squared value difference between the dummy face pattern and the human face pattern and between the inverted dummy face pattern and the inverted human face pattern across subjects 1–10. There was no significant difference between the dummy face pattern and the human face pattern at P7 for N200 ($t = -1.0888$. $p > 0.05$), Pz for P300 ($t = -0.9172$, $p > 0.05$) and Fz for N400 ($t = -0.3762$, $p > 0.05$), and between the inverted dummy face pattern and the inverted human face pattern at Pz for P300 ($t = -0.2348$, $p > 0.05$). However, compared to the inverted human face pattern, the inverted dummy face pattern obtained significantly higher *R*-squared value of N200 at P7 ($t = -2.1108$, $p < 0.05$), and N400 at Fz ($t = -3.9432$, $p < 0.05$).

Table 2 shows the online classification accuracy and information transfer rate based on an adaptive strategy (Jin et al., 2011). A paired samples *t*-test method was used to show the classification accuracy ($t = -0.7679$, $p > 0.05$) and RBR ($t = -0.9496$, $p > 0.05$) difference between the dummy face pattern and the human face pattern. It was also used to show the classification accuracy ($t = -0.4814$, $p > 0.05$) and RBR ($t = -0.8321$, $p > 0.05$) difference between the inverted dummy face pattern and the inverted human face pattern. It showed that there was no significant difference between the dummy face and the human face pattern, and between the inverted dummy face patterns and the inverted human face pattern. The average classification accuracies of the upright dummy face pattern and inverted dummy face pattern are equal. A paired samples *t*-test method was used to show the classification accuracy ($t = 0.2097$, $p > 0.05$) and RBR ($t = -0.1363$, $p > 0.05$) difference between the upright dummy face pattern and inverted dummy face pattern. There was no significant difference.

4. Discussion

In this paper, four different paradigms were presented to survey the difference between the dummy and human face stimulus. It was reported that the human faces and the inverted human faces yielded good performance when they were applied to BCIs (Jin et al., 2012a,b; Kaufmann et al., 2011; Zhang et al., 2012). It would be interesting to survey that whether there were significant difference between the dummy face pattern and the human face pattern when they were applied in BCI system. In this paper, the dummy face pattern was used to compare with the human face pattern, and the inverted dummy face pattern was used to compare with the inverted human face pattern. The results showed there were no significant difference on ERP amplitude, classification accuracy and information transfer rate among the dummy face patterns and the human face patterns.

4.1. Amplitude and latency of ERPs

Firstly, statistical analysis was used to show the difference between the dummy face pattern and the human face pattern, and between the inverted dummy face pattern and the inverted human face pattern at P7 for N200, Pz for P300 and Fz for N400. Fig. 6A, C and E showed that there were no significant differences at P7 for N200, Pz for P300 and Fz for N400 between the human face pattern

Table 2
Performance from online feedback runs using two trials to construct the average. In this table, 'Acc' refers to classification accuracy and 'RBR' to raw bit rate, measured in bits/min. 'DF-P' denotes the dummy face pattern, 'HF-P' denotes the human face pattern, 'IDF-P' denotes the dummy face pattern and 'IHF-P' denotes the inverted face pattern.

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average
Acc (%)	DF-P	100	95.8	95.8	91.7	100	83.3	100	100	87.5	87.5	94.0 ± 6.0
	HF-P	95.8	95.8	87.5	95.8	100	87.5	95.8	100	100	100	95.8 ± 4.8
	IDF-P	100	95.8	87.50	91.7	100	70.8	100	100	95.8	95.8	94.0 ± 9.0
	IHF-P	100	91.7	91.7	91.7	100	83.3	91.7	100	100	95.8	95.0 ± 6.0
RBR	DF-P	40.4	34.3	31.8	35.3	42.2	18.8	37.4	43.1	27.4	22.8	33.4 ± 8.2
	HF-P	36.5	34.3	24.0	39.0	38.9	26.3	35.0	42.2	41.3	41.3	35.9 ± 6.3
	IDF-P	41.3	31.8	26.3	29.7	40.4	15.9	41.3	42.2	31.2	35.8	33.6 ± 8.4
	IHF-P	41.3	27.6	30.3	50.8	40.4	19.5	29.2	42.2	42.2	35.8	35.9 ± 9.2

and the dummy face pattern ($p > 0.05$). Fig. 6B, D and F showed that there were no significant differences between the inverted dummy face pattern and the inverted human face pattern at P7 for N200, Pz for P300 and Fz for N400 ($p > 0.05$). We also calculated the R-squared values of N200 at P7, P300 at Pz and N400 at Fz from subjects 1–10 for the four conditions. It was found that the inverted dummy face pattern obtained significantly higher R-squared value than the inverted human face pattern at P7 for N200 ($p < 0.05$) and at Fz for N400 ($p < 0.05$). However, online feedback did not show significant difference on classification accuracy between the inverted dummy face pattern and the inverted human face pattern.

Secondly, we calculated the correction of ERP amplitude showed in Fig. 5, the result showed that there were high correction on amplitude between the dummy face pattern and the human face pattern at P7 ($R = 0.8710$, $p < 0.05$), Pz ($R = 0.9119$, $p < 0.05$) and Fz ($R = 0.8842$, $p < 0.05$), and between the inverted dummy face and the inverted human face pattern at P7 ($R = 0.8116$, $p < 0.05$), Pz ($R = 0.9545$, $p < 0.05$) and Fz ($R = 0.8991$, $p < 0.05$).

Although it was shown that the averaged latencies of N200 at P7, P300 at Pz and N400 at Fz evoked by the dummy face stimulus were latter than that evoked by the human face stimulus in Table 1, there were no significant difference of latencies between the dummy face pattern and the human face pattern at P7 for N200 ($t = 0.3683$, $p > 0.05$), Pz for P300 ($t = 1.3529$, $p > 0.05$) and Fz for N400 ($t = 0.5275$, $p > 0.05$), and between the inverted dummy face and the inverted human face at Fz for N400 ($t = 0.5275$, $p > 0.05$). But it was found that the ERP latency of the inverted dummy face pattern was significantly latter than the inverted human face pattern at P7 for N200 ($t = 2.7526$, $p < 0.05$) and at Pz for P300 ($t = -2.4369$, $p < 0.05$).

4.2. Online feedback

We also tested the online performance of the dummy face and the human face for upright and inverted forms. The results showed that there were no significant difference between the dummy face pattern and the human face pattern for the upright form in terms of classification accuracy ($t = -0.7679$, $p > 0.05$) and information transfer rate ($t = -0.9496$, $p > 0.05$) and for the inverted form in terms of classification accuracy ($t = -0.4814$, $p > 0.05$) and information transfer rate ($t = -0.8321$, $p > 0.05$). It indicated that the dummy faces stimuli could obtain as good performance as the human faces stimuli when they were applied in BCI systems.

All these results indicated that the dummy faces would be a good choice to replace the human faces. It was reported that the small changes of dummy face could lead to different expressions which would help to improve the performance of BCI systems (Jin et al., 2014). This work showed one of the potential value of the dummy face when it was used in BCI systems. Furthermore, the dummy face could be edited more easily than the human face which would help us to find other superior forms of the faces when it was used in BCI systems. Moreover, dummy faces would not have copyright infringement problems, so we could design the faces forms and select the different faces freely.

5. Conclusions

In this paper, the results showed that there was no significant difference between the dummy pattern and the human face pattern for both the upright and inverted forms on ERPs, classification accuracy and information transfer rate. In the next step, we would survey the dummy faces in different forms both on patients and health subjects to validate the performance of the BCIs based on dummy faces stimuli further. The dummy faces used in this paper were only drawn by the lines and curves, which could be called a simple face. We would further survey the complex dummy faces, which may lead to evoking different ERPs.

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