Pattern Recognition 46 (2013) 1159–1169

Contents lists available at SciVerse ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/pr

Person authentication from neural activity of face-specific visual self-representation

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ARTICLE INFO

Article history:
Received 26 January 2012
Received in revised form
11 September 2012
Accepted 24 October 2012
Available online 7 November 2012

Keywords:
Biometrics
Person authentication
Electroencephalography (EEG)
Face-specific visual self representation

ABSTRACT

In this paper, we propose a new biometric system based on the neurophysiological features of face-specific visual self representation in a human brain, which can be measured by ElectroEncephaloGraphy (EEG). First, we devise a novel stimulus presentation paradigm, using self-face and non-self-face images as stimuli for a person authentication system that can validate a person's identity by comparing the observed trait with those stored in the database (one-to-one matching). Unlike previous methods that considered the brain activities of the resting state, motor imagery, or visual evoked potentials, there are evidences that the proposed paradigm generates unique subject-specific brain-wave patterns in response to self- and non-self-face images from psychology and neurophysiology studies. Second, we devise a method for adaptive selection of EEG channels and time intervals for each subject in a discriminative manner. This makes the system immune to forgery since the selected EEG channels and time intervals for a client may not be consistent with those of imposters in terms of the latency and amplitude of the brain-waves. Based on our experimental results and analysis, it is believed that the proposed person authentication system can be considered as a new biometric authentication system.

1. Introduction

As personal security and public safety become hot issues, biometric systems that automatically recognize individuals based on their physiological or behavioral characteristics have received great interest during the past couple of decades. Many research groups have devoted their efforts to achieve person identification or authentication by using various types of biometric traits.

While some biometric characteristics that are exposed to the outer world, such as the face [1], hand geometry [2], fingerprints [3], iris [4], signature [5] and gait [6], have been or are being used successfully in many applications, they are known to be vulnerable to fraud (e.g., fake fingers). For this reason, recently, internal biometric traits of the ear force field [7], veins [8], heart signals [9], odor [10], and brain signals [11–20] have been considered as alternative or supplementary characteristics to circumvent the problem of fraud.

Of the internal biometric traits, brain signals have emerged as a prominent characteristic. Previous studies have found that the brain activity of an individual is determined by the individual's unique pattern of neural pathways and thus it can be used for biometrics [11]. The main advantage of using brain signals as a biometric identifier is that it is one of the most fraud resistant. It is known that it is impossible to imitate the brain activity of any subject due to the fact that the neural pathways of a subject are unique and can never be found, even with state-of-the-art technologies [21]. Furthermore, brain electrical activity is ineffective under coercion from aggressors, since it is greatly influenced by stress [14], which means that it can be a very good trait for biometric authentication.

There exist various brain imaging techniques that can measure brain activity in a non-invasive manner, namely, functional Magnetic Resonance Imaging (fMRI), Positron Emission Topography (PET), MagnetoEncephaloGraphy (MEG), or ElectroEncephaloGraphy (EEG). In this paper, we use EEG thanks to its high temporal resolution, low cost, portability, and ease of setup for measurements compared to the other techniques.

In terms of generating a specific brain activity or pattern for biometrics, three kinds of stimulus types have been considered in the literature; (i) a resting state, not performing an explicit task [11–13], (ii) an imagined body-part movement, called motor imagery, [14–16], and (iii) Visual Evoked Potential (VEP), an evoked potential caused by a visual stimulus such as an alternating checkerboard pattern on a computer screen [17–20]. Table 1 summarizes the previous work on EEG-based biometrics with respect to the different stimulus types. It lists the various approaches along with their system types, which are either authentication or identification.

One of the earliest examples of biometrics based on brain signals was Paranjape et al.'s work [11]. They considered brain signals measured while both resting with eyes closed and resting with eyes open, and used the autoregressive model for the identification of 40

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http://dx.doi.org/10.1016/j.patcog.2012.10.023

Table 1
Approaches of the previous studies for EEG-based biometrics.

Authors	Stimulus	System type and method
Paranjape et al. [11]	Resting state	Identification, AutoRegressive (AR) models of various orders
Miyamoto et al. [12]		Authentication, spectral feature extraction from the EEG based on the distribution of spectra
Zhao et al. [13]		Identification, AR models, features from power spectrum, and k nearest neighbor method
Marcel et al. [14]	Motor imagery	Authentication, a statistical framework based on Gaussian mixture models and maximum a posteriori model adaptation
Hu [15]		Identification and authentication, AR models, moving average, and an artificial neural network
Xiao et al. [16]		Identification, feature extraction based on Fisher distance and multilayer neural networks
Palaniappan et al. [17]		Identification, use of the energy of the gamma band VEP potentials for features using an Elman neural network
Das et al. [18]	Visual Evoked Potential (VEP)	Identification, use of spatio-temporal filter, SVM, and LDA
Ferreira et al. [19]		Identification, a Welch's periodogram method and a multiclass SVM
Ferreira et al. [20]		Identification, multi-class SVM with radial basis function

subjects. Miyamoto et al. proposed spectral features for more practical applications with less computational load. They used EEGs recorded at rest with eyes closed in which the alpha rhythm was yielded [12]. Zhao et al. used a single electrode to measure brain signals evoked during relaxation with eyes closed and extracted the alpha power features from the EEG for individual identification [13].

Marcel et al. built a dataset from nine normal subjects, who performed mental imagination tasks of self-paced left-hand or right-hand movement for authentication. They used a statistical framework based on Gaussian mixture models and maximum a posteriori model adaptation [14]. Hu also performed research on motor imagery based biometrics and used an autoregressive and moving average model to fit the EEG data. He trained multilayer back-propagation neural networks for both identification and authentication [15]. More recently, Xiao and Hu applied a second-order blind identification to preprocess EEGs for enhancement of the signal-to-noise ratio and extracted features using the Fisher distance [16].

Palaniappan et al. carried out person identification with EEGs recorded from 102 subjects, who were asked to recognize and remember a picture that was shown, analyzing the VEP measurements coming from 61 active channels [17]. They also performed a rigorous analysis involving increased bandwidth, spatial averaging, multiple signal classification-based dominant frequency and power content estimation, and feature vector classification. Das et al. recorded VEP signals from 20 subjects and extracted discriminative spatio-temporal filters [18]. And they exploited Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) for discriminating individuals based on their brain activity. Last but not least, Ferreira et al. experimented with person identification using EEGs recorded during a perception or mental task [19]. They proposed a classifier with memory without increasing the computational complexity. Ferreira et al. also used superimposed face and house with equivalent discriminability to induce VEP signals [20]. They collected the dataset from 13 female subjects and classified by multiclass SVM with radial basis function.

While the above mentioned studies presented successful performance in their own work, there is no clear evidence that proves the uniqueness of brain signals activated by those stimuli from an individual. Meanwhile, in this paper, we utilize neuronal activities elicited by self- or non-self-face images, for which there are clear neurophysiological evidences in both EEG [22–24] and fMRI [25–27] studies that a human brain responses distinctly. Based on those studies, we believe that the stimulus type of face images are appropriate to evoke subject-specific brain activities.

The main contributions of this paper are two-fold. First, we propose a novel stimulus representation paradigm for EEG-based person authentication, which validates a person's identity by comparing the observed biometric with those stored in the database (one-to-one matching). Self-face and non-self-face images are used as stimuli. Unlike the previous methods, we can demonstrate that the proposed paradigm generates a unique subject-specific brain-wave pattern, which also agrees with studies in psychology and neurophysiology [22–27]. In terms of the universality, distinctiveness, permanence, collectability and uniqueness [28], it is believed that the brain signal evoked by the face-specific visual self representation is well qualified as a biometric. Second, we devise a method to adaptively select channels and time intervals for each subject in a discriminative manner. It is known that Event-Related Potential (ERP) components vary across subjects in terms of their latency, amplitude, or shape, which results from the inherent subject-to-subject variation of neural pathways in the brain [29]. Therefore, it is necessary for a method to extract subject-dependent features by considering both channels and time intervals that are highly responsive to a stimulus. A preliminary partial version of this work was presented in [31]. Compared to the paper, this work proposes a new feature extraction method and performs experiments on a larger dataset including data from a pair of monozygotic twin.

The rest of the paper is organized as follows. We start by introducing neuro-physiological evidence for face-specific visual self representation in Section 2. We propose a novel experimental paradigm to elicit brain signals for person authentication based on a self-face representation and a method of selecting channels and time intervals adaptively for each subject in Section 3. The experimental results and analysis are described in Section 4. Finally, concluding remarks are made and further research issues are outlined in Section 5.

2. Neurophysiological evidence

Psychological and neurophysiological studies on self-recognition in a human brain have found that the brain activity response to one's own face is markedly different from the response to familiar or unfamiliar non-self-faces. First, fMRI studies of the cortical networks have shown that self-face can be a representative stimulus for visual self-representation [25–27]; the right inferior frontal, precentral, supramarginal, and bilateral ventral occipito-temporal cortices are highly responsive to self-face images. The results suggest that observed Blood-Oxygen-Level Dependence (BOLD) responses are possible evidence of face-specific visual self representation.

Meanwhile, EEG studies have evidenced that there are meaningful differences in the responses to faces in terms of the time-series pattern and face-specific ERP components, namely, N170 and N250 [22–24]. Fig. 1 shows the change of the electrical signals in response to the face stimuli, i.e., the self-face and non-self-face images, by the proposed stimulus paradigm described in the following section that was measured at electrode site P4, positioned on the parietal cortex, for Subject 1 in our dataset. An N170, a negative deflection occurring at around 140–200 ms after the onset of the stimulus presentation, is apparent for faces compared to other objects. An N250 component is observed in the inferior temporal areas and posterior area, which are known to be responsive to memory-related face processing and are highly sensitive to different types of familiar faces such as famous faces, personally known faces, and experimentally learned faces [22]. Tanaka et al. have shown that the subject's own face produced a N250 in posterior area relative to nontarget faces. Interestingly, the ERPs somewhat overlap until 250 ms, but at that point a clear difference emerges between the ERPs for the self-face and non-self-face images. This neurophysiological feature motivates us to utilize the electrical brain signals evoked by the face-specific visual self representation in a human brain for person authentication.

3. Biometrics based on face-specific self representation

Based on the neurophysiological evidence explained above, we believe that the electrical brain activities elicited by self-face and non-self-face stimuli can be used as a new biometric. In this section, we propose a novel EEG-based person authentication system that uses the face-specific visual self representation of a human brain and also devise a method of optimized channel and time-interval selection for subject-dependent feature extraction.

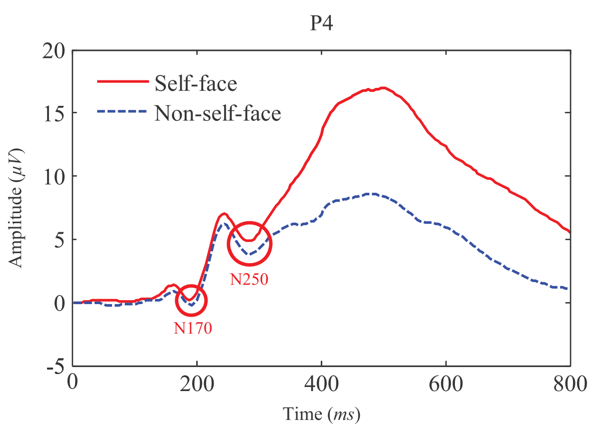

Fig. 1. Visualization of the change of the electrical signals including face-specific ERP components responding preferentially to self-face and non-self-face images at P4 positioned on the parietal cortex.

3.1. Proposed experimental paradigm

In this paper, self-face and non-self-face images are used to stimulate a subject's brain activity. A self-face image denotes a target subject's own face image while non-self-face images include both familiar faces such as his/her friends and unfamiliar ones whom he/she has never seen before. Here, we should note that in the case of self-face, the same face image is presented as a stimulus but, in the case of non-self-face, different face images are presented each time to remove the effect of adaptation. Meanwhile, in the case of an imposter, the imposter knows the forgery target person to authenticate in advance.

Once an experiment starts, a blank white screen with a red fixation cross is presented for 4000 ms to inform a subject of the start of the experiment. Then a face image and a blank screen are displayed in turn for 150 ms and 1500−2000 ms, respectively, as presented in Fig. 2(a). A random sequence of self-face and non-self-face stimuli is given to the subject so as to avoid the effect of the subject predicting the next stimulus. Note that while the face image is given for a fixed time duration, the duration of the blank screen is random and ranges between 1500 and 2000 ms, for the same reason as given above. Fig. 2(b) presents a schematic diagram of the proposed experimental paradigm. Throughout the experiment, the subject was required to fixate his or her attention on the cross and to classify the stimuli into either 'self' or 'non-self' as correctly as possible.

3.2. Methodology

On the one hand, the high variability of EEG signals across subjects is a good and useful characteristic in terms of person authentication, on the other hand, this fact makes it difficult to extract discriminative features from the signals in terms of pattern recognition. In order to handle this problem, we propose a subject-specific feature extraction method that operates in a subject-dependent way by using the brain-wave patterns evoked by self-face and non-self-face images, each of which is called a 'self' class and a 'non-self' class throughout the paper.

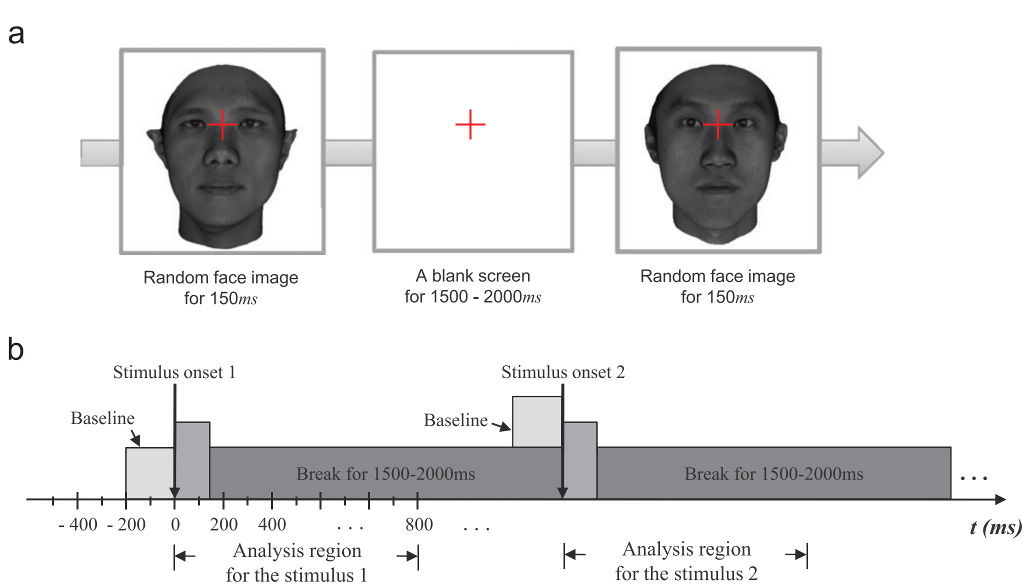

Fig. 2. The proposed experimental paradigm to stimulate brain activities for person authentication based on face-specific visual self representation. (a) An example of stimulus presentation. (b) A timing scheme of the experimental paradigm.

3.2.1. Channels and time intervals selection

For the analysis and classification of time-varying EEGs, one of the main issues is extracting features from channels and time-intervals with as high reliability in the database as possible. Increasingly, from a machine learning point of view, it is important to find discriminative features in an automatic person authentication system, which needs a subject-dependent classifier construction to make the system robust to forgery. This raises the question of how to measure or determine the discriminative power of various features.

Although there is a neurophysiological phenomenon in which the electrical potentials evoked by self- and non-self-face images show a clear difference in amplitude from some point after the onset of the stimuli, as shown above, the point at which the difference between the potentials emerges is highly variable across subjects with regard to the channel and time interval, due to their presumable difference of cortical networks (see Fig. 3). In order to tackle this problem, we propose a method of selecting subject-specific EEG channels and a time interval in which the discriminative patterns appear.

In this paper, we apply the pointwise biserial correlation coefficient (also called the r-value) [32], which is a special form of the Pearson product-moment correlation coefficient and gives information about the magnitude of the correlation as well as the direction of the relationship. It is defined as follows:

$$r(t) = \frac{\sqrt{N_1 N_2}}{N_1 + N_2} \cdot \frac{M_1(t) - M_2(t)}{S(t)} \tag{1}$$

where $t \in \{1, \ldots, T\}$, T is the length of the time of interest and N_1 and N_2 denote, respectively, the total number of trials of the 'self' class and the 'non-self' class. Meanwhile, $M_1(t)$ and $M_2(t)$ are, respectively, the mean values for all trials in both classes at the time of interest, t, and $S(t)$ represents the standard deviation when simultaneously considering the sample distributions of all trials of both classes. According to the definition, the further apart the features of two dichotomous classes and/or the smaller the variance, the larger the r-value becomes.

Therefore, we believe that channels and time intervals with high r-values are a relatively important domain for authentication. However, how should their relative importance be determined? A statistical significance test is a good and appropriate tool for this problem. We apply a one-tailed t-test to calculate the correlation coefficient for all the channels as follows:

$$v = \frac{r(t)\sqrt{N-2}}{1 - r(t)} \tag{2}$$

where v denotes a t-value, N is the total number of trials in the two classes ($N-2$ is the degrees of freedom), and $r(t)$ is the point-biserial correlation coefficient at the time of interest, t, as calculated by Eq. (1).

The time intervals whose t-values are larger than a critical parameter obtained from the p-value, which determines the level of significance, are considered as the meaningful domain. After we have selected meaningful time intervals for each channel, we then sort them in a descending order based on the mean squares of the r-values with respect to the channels. Finally, the top K number of channels, where K is a predetermined number, are considered for the ensuing processes. From here on, let us denote the selected channel set as C. An illustrative diagram for the subject-dependent channel and time interval selection is presented in Fig. 4.

From the studies of psychophysics and neurophysiology, it is known that visual information is processed in a feedforward manner starting from the primary visual cortex to the secondary visual cortex, to the inferotemporal cortex, and thence to areas in the frontal cortex [33]. The selection of a time interval for each channel individually can reflect the important feature of the time delay during visual processing in the human brain. We can also expect two main effects from the proposed method: (i) The selection of subject-specific discriminative channels and time intervals can improve the performance of a person authentication system. (ii) It makes a system immune to forgery since the selected channels and time intervals from a client may not be consistent with those from imposters. In other words, although the same stimuli are presented, the ERPs including the components such as N170, N250, and P300 are inherently variable across subjects in terms of latency and amplitude [29].

3.2.2. Feature extraction and classification

Since the brain signals are highly variable across inter-trials even for the same subject, we take an average of the electrical potentials of each class per trial over the repeated stimulation. We then compute the difference of the averaged signals in response to self-face and non-self-face images for feature extraction as follows:

$$\mathbf{d}_{c,i} = \frac{1}{n_1} \sum_{j \in SF} \mathbf{s}^j_{c,i} - \frac{1}{n_2} \sum_{j \in NSF} \mathbf{s}^j_{c,i} \tag{3}$$

where $\mathbf{d}_{c,i}$ denotes the difference of the averaged signals, $\mathbf{s}^j_{c,i}$ denotes an average EEG of channel c in the i-th trial, which includes only the channels and the time intervals selected by the proposed method mentioned above, and n_1 and n_2 are, respectively, the number of times that 'self-face' (SF) and 'non-self-face' (NSF) stimuli are given per trial. This is one of the features that we use for authentication, called a 'temporal feature'.

In addition to the temporal feature, we also consider a 'dynamic feature' [29,30]. EEG changes associated with an external stimulus are often characterized by its time domain components: positive/negative peaks at specific latencies of the signal, or even the shape of EEG patterns. Generally, the EEG temporal

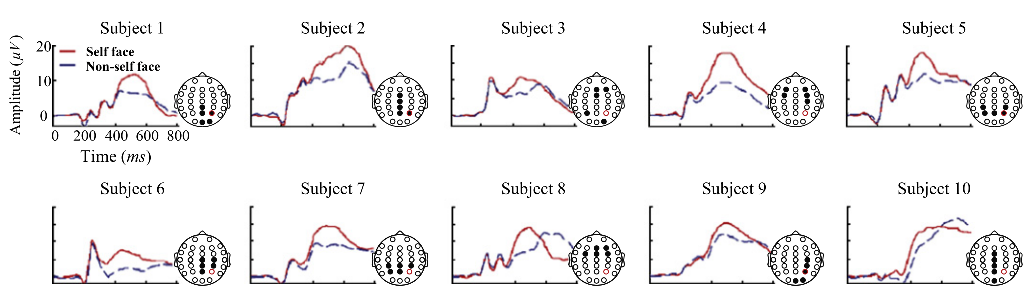

Fig. 3. Comparison across averaged ERPs for each subject at the same channel P4 (red circle in the topological map). The circles filled with black in topological maps indicate the selected channels for each subject by using the proposed method. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

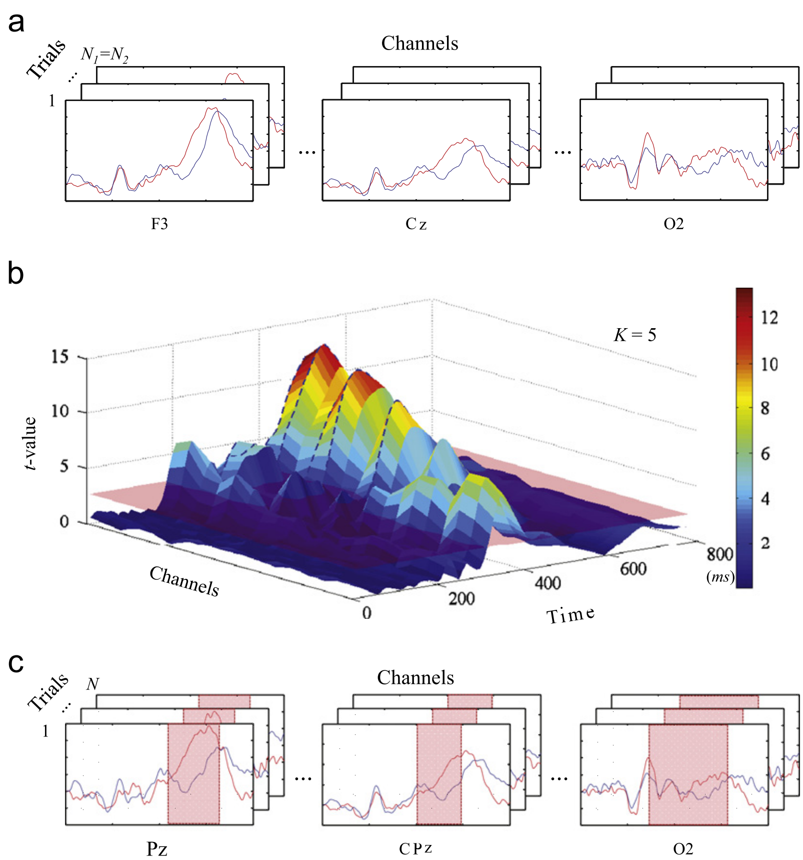

Fig. 4. Schematic flow of the proposed method to select discriminative channels and time intervals: (a) preprocessed EEG signals evoked by self-face and non-self face images for each channel, (b) t-value map (the meaningful time intervals for each channel are selected based on the critical p-value (red shaded region) and the top K ranked channels (blue dotted lines) are considered ($K=5$) for further processing), (c) feature extraction only from the selected channels and time intervals (red shaded regions). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

dynamics is one of the most important discriminative features between different types of EEG patterns. The dynamic feature gives information about the flow of changes in the EEG. For this purpose, we used a least squares estimate of the time derivative Δd for each channel. The dynamic feature is defined as follows:

$$\Delta d_{c,\,i}(t) \approx A \sum_{m=-W}^{W} m d_{c,i}(t+m) \quad \text{s.t. } t > W \tag{4}$$

where $\Delta d_{c,i}(t)$ denotes a sample point of the i-th trial in a selected channel c at time t, $c \in C$, C denotes the selected channel set, A is a normalization constant, and W is the half size of the window.

The concatenation of the two feature vectors is composed as follows:

$$\mathbf{x}_i = [\mathbf{d}_{c,\,i}^{\dagger},\ \Delta\mathbf{d}_{c,\,i}^{\dagger}], \quad \forall\, c \in C \tag{5}$$

where † denotes a vector transpose operation, which is fed into a non-linear SVM [34] classifier. It has already been shown that non-linear SVM is robust for synchronous EEGs classification [35].

During evaluation, the decision function for a non-linear SVM classifier is in the form of

$$f(\mathbf{x}) = \mathrm{sgn}\left(\sum_{i=1}^{n} y_i \alpha_i k(\mathbf{x},\mathbf{x}_i) + b\right) \tag{6}$$

where $y_i \in$ {1('self-face'), −1('non-self-face')} denotes a class label, $\mathbf{x}$ is a test EEG signal, $\mathbf{x}_i$ is a support vector, and α_i and b denote, respectively, a Lagrangian multiplier and a bias. In Eq. (6), k is a kernel function, for which, in this paper, we utilize a Gaussian function defined as

$$k(\mathbf{x},\mathbf{x}_i) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}_i\|^2}{2\sigma^2}\right) \tag{7}$$

where σ is the bandwidth of the Gaussian kernel.

4. Experimental results and analysis

4.1. Data acquisition and signal processing

In order to present the effectiveness and feasibility of the proposed method, we collected EEG data from 10 healthy Korean students, including 1 pair of monozygotic twin, who were between 20 and 29 years old (mean 26.6 ± 6.7, males). All of the subjects were right-handed and had normal or corrected-to-normal visual acuity. No subjects had any history of neurological or psychiatric disorders, substance abuse, or other serious medical conditions.

The face images presented to subjects as stimuli were acquired sing a 3dMD face capture system with the same illumination conditions for all subjects [36]. The subjects were asked to make a neutral facial expression facing towards the camera. All the face images were processed to remove external features such as hair, cropped into a common oval frame which was placed on a white uniform background, and scaled to the size of 400×400 pixels. Fig. 5 shows 28 examples of the 45 face images used in our experiment.

We used a Neuroscan SynAmps2 and a BCI2000[1] for the EEG recording. Subjects were seated comfortably in a chair with armrests

[1] http://www.bci2000.org.

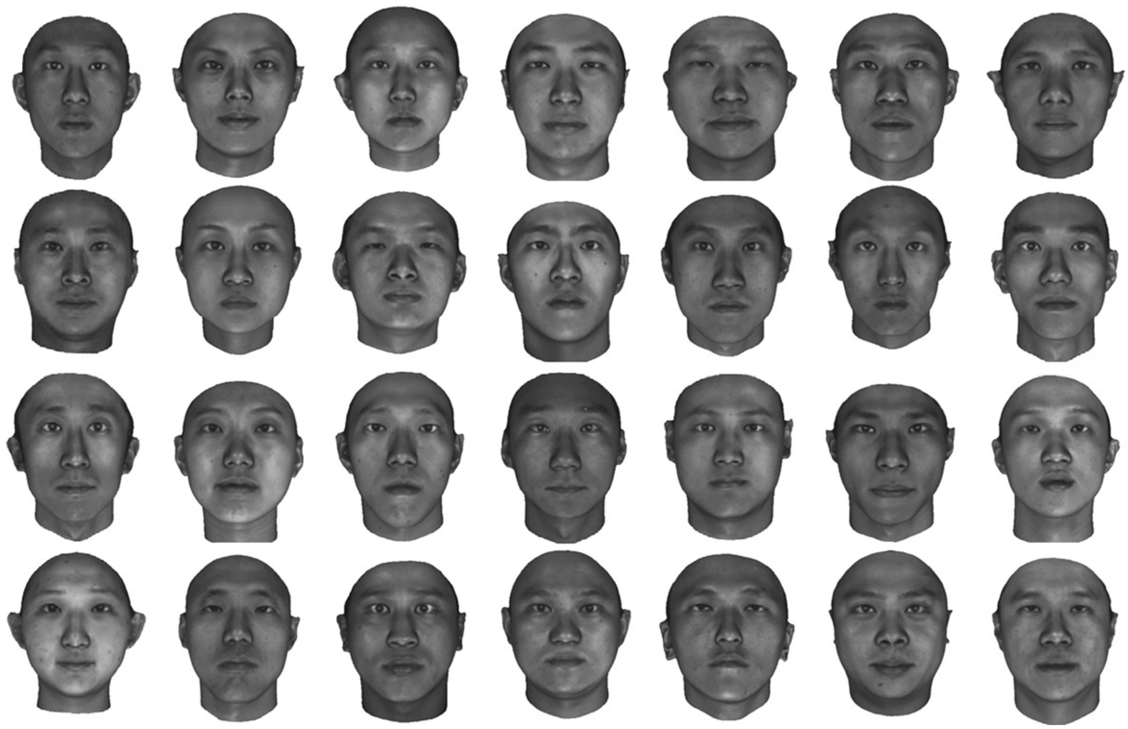

Fig. 5. Examples of the face stimuli used in the experiment.

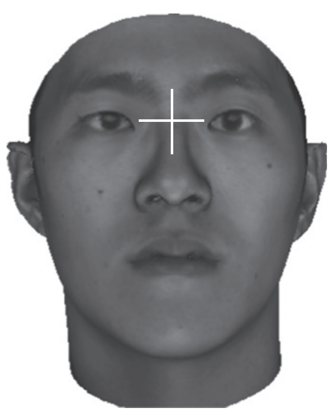

Fig. 6. A sample stimulus image: a cross located in the middle of the forehead denotes a fixation point used to minimize eye movements during experiments.

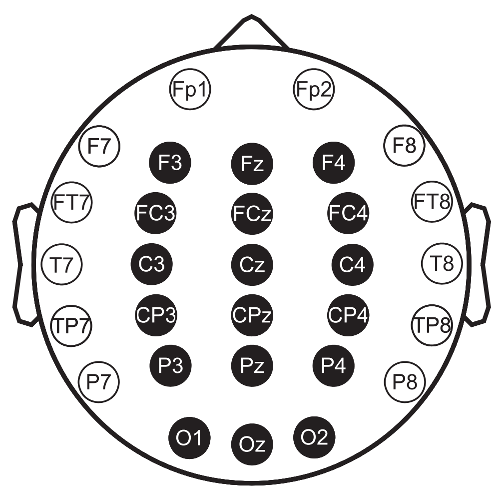

Fig. 7. The selected electrode locations of the International 10–20 system. (The black-filled circles denote the channels used in this paper.)

in a quiet room at a distance of 1 m from the monitor, which corresponds to an angle range from -10° to 10°. The stimulus is displayed in the center of the screen and the subjects were asked to fixate on the red cross, positioned in the middle of the eyes on the stimulus image, so as to minimize the eye movement [24]. Fig. 6 represents a sample stimulus image in our experiment.

The EEG signals were recorded from 18 scalp electrodes, positioned according to the 'International 10–20 System', as shown in Fig. 7 where the channels used are marked with black-filled circles, following the convention of previous studies of self representation in psychology [22–24]. The signals were acquired at a sampling rate of 250 Hz and were band-pass filtered between 0.1 and 100 Hz. In addition, a 50 Hz notch filter was applied to remove power line contamination.

The dataset was composed of EEG signals from two sessions conducted on different days. Each session included two runs separated by short breaks and each run was further composed of 50 trials, in total 100 trials per session. For each trial, a total of 20 face images were presented: 10 of self-face and 10 of non-self-face images.

All the signals were baseline corrected by subtracting the mean of the samples at 200 ms before stimulus-onset, because during recording, an EEG undergoes a slow shift over time, such that the zero level might differ considerably across trials. While in raw EEG signals the onset- and/or offset-related responses were observed, we were filtered out by the preprocessing of 30 Hz low-pass filtering. That is why those responses are not observed in the averaged ERP. In this work, the 30 Hz selection of low-pass filtering was based on Miyakoshi et al.'s work. The EEG data was then down-sampled using a moving average method. The samples taken between 0 and 800 ms after stimulus-onset were considered for training and evaluation (see Fig. 2(b)). The dataset used in this paper is available at http://image.korea.ac.kr/code_db.

4.2. Averaged event-related potential (ERP)

We first check the neurophysiological phenomena associated with face-specific visual self-representation in a human brain. The averaged ERPs can show class-discriminative EEG signal patterns between self-face and non-self-face images, which are subject-dependent. Fig. 8 presents the electrical potentials evoked by self-face and non-self-face images for a real client case. It clearly shows that ERPs for the self-face stimulus were distinguished from those for the non-self-face one. Especially, the difference between familiarity levels is less defined until about 250 ms, at which point a difference emerges in each channel. As a reference, the mean amplitude of ERPs for the face is in accordance with those measured in the previous work [22–24]. It is interesting that the average ERPs measured in our Korean dataset is similar to those of the Caucasian dataset. From this fact, we can conjecture, while not experimentally proved, that the self-representation is valid across ethnicities.

It has also been noticed that for the imposter case (see Fig. 9), while we can see face-specific components such as N170 over the posterior area and N250 over the inferior temporal area, there is no noticeable difference between self-face and non-self-face stimuli at the same time-bandwidth as in a real client case. This distinction between the cases of a real client and an imposter shows the advantage of the proposed EEG-based person authentication method in terms of its immunity to forgery.

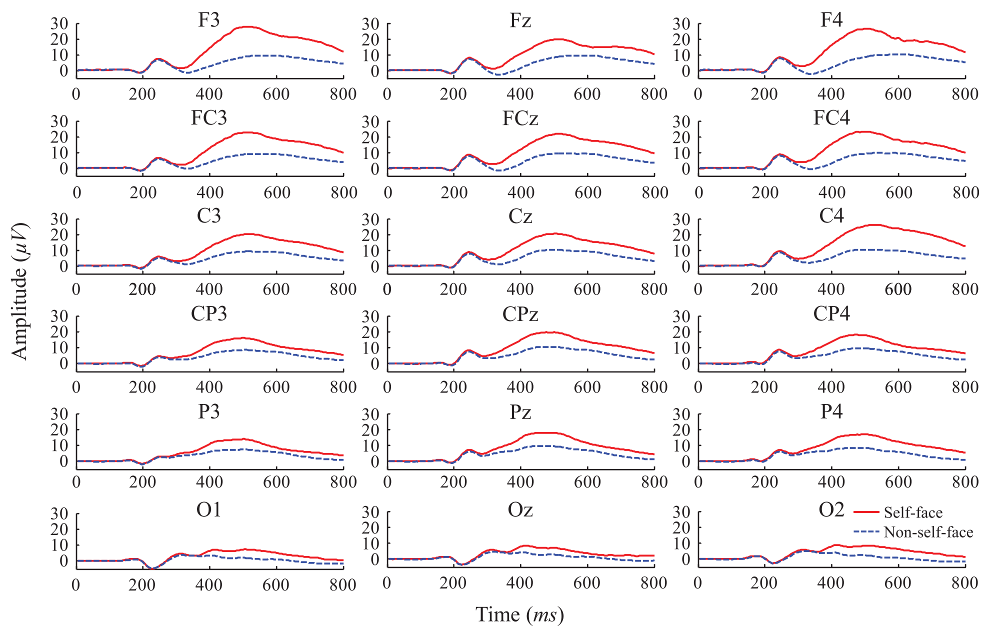

Fig. 8. Averaged ERPs of self-face (red solid line) and non-self-face (blue dotted line) images for a real client case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

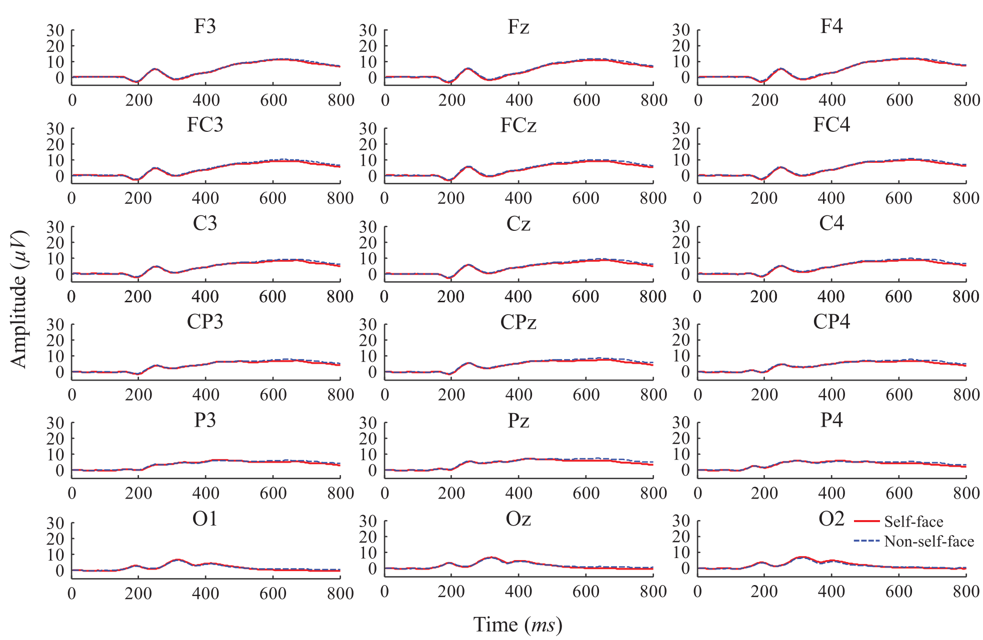

Fig. 9. Grand averaged ERPs of self-face (red solid line) and non-self-face (blue dashed line) images for the imposter case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

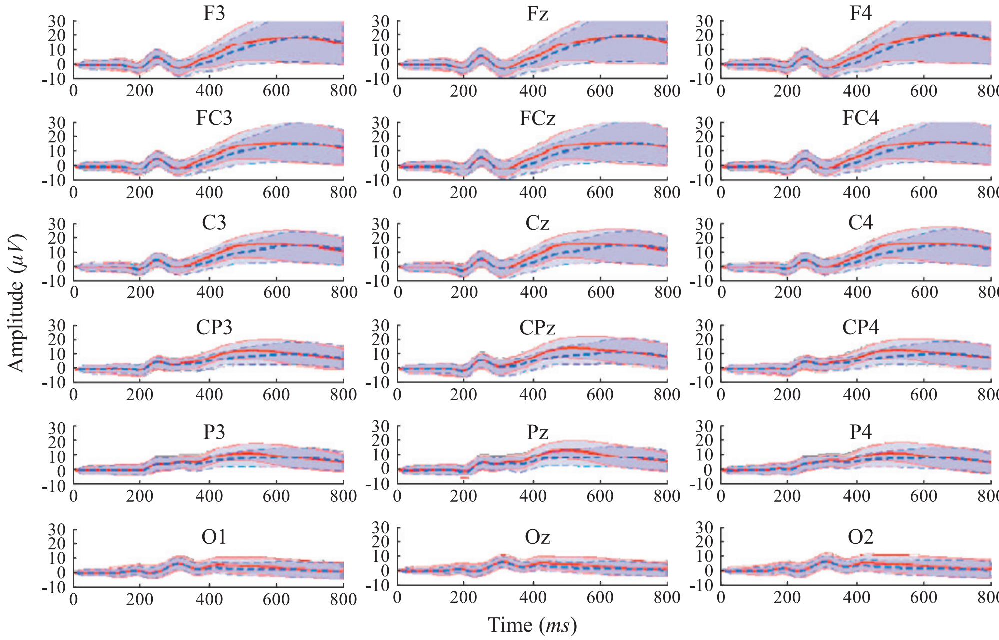

Fig. 10. Grand averaged ERPs (thick line) and standard deviation (thin line) for self-face (red solid line) and non-self-face (blue dashed line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Performance of the proposed person authentication method.

Subject	Accuracy (%)	FAR (%)	FRR (%)
Subject 1	93.7	7.7	5.0
Subject 2	94.9	4.7	5.6
Subject 3	79.4	20.2	21.1
Subject 4	84.5	18.1	13.1
Subject 5	86.6	10.2	16.6
Subject 6	77.6	22.6	22.4
Subject 7	76.9	22.9	23.4
Subject 8	95.3	4.7	4.7
Subject 9	82.4	16.1	19.2
Subject 10	89.2	9.7	12.0
Mean(STD)	**86.1(7.3)**	**13.9(7.7)**	**13.9(7.5)**

Meanwhile, Fig. 10 shows the grand averaged ERPs and standard deviation for self- and non-self-face from all scalp EEG channels. From this figure, we can clearly see that there exists individual difference of ERP patterns for the face processing exists and therefore the selection of the subject-specific channel and time interval must be considered to gather discriminative features in a person authentication system.

4.3. Performance and results analysis

For the evaluation of the proposed method, we performed a 10-fold cross validation for which we randomly selected 180 trials for training and used the remaining 20 trials for evaluation. Table 2 shows the performance of the proposed EEG-based person authentication. Based on the results, we can say that the brain activities related to face-specific visual self-representation are a useful biometric for person authentication.

Table 3 shows a comparison of our method with previous works on EEG-based person authentication. Whereas, for example, Marcel et al. [14] showed a maximum accuracy of 80.7% with a False Acceptance Rate (FAR) of 14.4% and a False Rejection Rate (FRR) of 24.3%, the proposed method produced, on average, a high accuracy of 86.1%, a low FRR of 13.9%, and a slightly low FAR of 13.9%. Also, with respect to the number of clients and the total number of trials per subject considered in an experiment, we can say that the experimental results using the proposed method are more reliable than those produced by previous works.

In Table 4, we present the selected channels and time intervals in a descending order (K=5) with respect to the mean squares of the r-values for each subject. We found that the selected channels, which have high discriminative electrical potentials between self-face and non-self-face images, are mostly distributed around the frontal areas (which involve conscious thought, voluntary movement, and personality), the central areas (which are responsible for most 'higher order' or intellectual brain functions such as thinking, reasoning, judging, planning, voluntary movement, and overall behavior), and the parietal areas (which process and interpret signals such as vision, hearing, motor skills, and memory), for all the subjects. Interestingly, we notice that although subjects performed the visual processing of the face images in a very similar manner, the selected channels and the time-intervals with relatively significant electrical potentials were remarkably distinctive for each subject. This result suggests that the proposed method can provide subject-specific features and a classifier with a high reliability. This finding also agrees with the previous EEG-based face-specific visual physiological studies [22–24].

In addition, we performed comparative analysis with Autoregressive (AR) coefficients which has been most widely used for feature extraction in the literature of the EEG based biometrics. After pre-processing including the channels and time interval selection, we conducted AR-based feature extraction for each subject's ERP signals response to only the self-face stimulus. To conclude, the proposed feature extraction method utilizing the difference between the averaged signals in response to self-face and non-self-face images is more robust for person authentication than the AR-based feature extraction method. Table 5 compares the results in terms of accuracy, FAR, and FRR. Although the AR-based method presented better performance for Subject 9, on average, the proposed method produced a higher accuracy of more than 15% with a much smaller standard deviation.

Table 3
Performance comparison with the previous works.

Author	Number of clients	Total number of data per subject[a]	Stimulus type	Accuracy (%)	FAR (%)	FRR (%)
Proposed method	10	200	Visual stimuli (self- and non-self-face)	**86.1**	**13.9**	**13.9**
Marcel et al. [14]	6	12	Motor imagery (left, right hand)	80.7	14.4	24.3
Hu et al. [15]	3	20–36	Motor imagery (left, right hand, foot, and tongue)	83.9	N/A	N/A
Miyamoto et al. [12]	23	10	Resting state (with closed eyes)	79	21	21

[a] For the details, refer to the original papers.

Table 4
Selected channels and time intervals for each subject ($K=5$).

Subject	Type	Channel ranks up to 5				
		1	2	3	4	5
Subject 1	Channel	Pz	Oz	CPz	P4	O2
	Time-interval (ms)	421–610	289–627	404–594	412–602	305–619
Subject 2	Channel	Pz	CPz	FCz	Cz	P4
	Time-interval (ms)	412–718	404–792	396–800	396–800	412–718
Subject 3	Channel	P3	O2	FCz	Fz	F4
	Time-interval (ms)	371–520	388–528	577–800	594–800	602–800
Subject 4	Channel	C4	FC4	FC3	F3	F4
	Time-interval (ms)	280–800	280–800	322–800	322–800	289–800
Subject 5	Channel	Pz	P3	P4	CP3	CP4
	Time-interval (ms)	396–610	396–602	412–577	396–586	412–561
Subject 6	Channel	CPz	Pz	C4	CP4	Cz
	Time-interval (ms)	322–685	322–652	330–709	322–701	330–685
Subject 7	Channel	Pz	CPz	CP4	P3	CP3
	Time-interval (ms)	338–652	346–635	346–635	404–643	412–635
Subject 8	Channel	FC4	Fz	FCz	F4	FC3
	Time-interval (ms)	569–800	536–800	569–800	536–800	569–800
Subject 9	Channel	P4	CP4	C4	Oz	O2
	Time-interval (ms)	363–676	355–676	478–668	412–627	478–627
Subject 10	Channel	CPz	Cz	Pz	Oz	FCz
	Time-interval (ms)	289–553	289–800	289–775	388–478	289–800

Table 5
Performance comparison between the proposed method and an AR-based feature extraction method (STD: standard deviation).

Subject	Proposed method			AR-based method		
	Accuracy	FAR	FRR	Accuracy	FAR	FRR
Subject 1	93.7	7.7	5.0	89.9	11.1	9.3
Subject 2	94.9	4.7	5.6	51.3	18.2	79.3
Subject 3	79.4	20.2	21.1	60.3	41.7	37.8
Subject 4	84.5	18.1	13.1	76.1	12.3	35.1
Subject 5	86.6	10.2	16.6	76.5	12.0	35.1
Subject 6	77.6	22.6	22.4	63.2	23.5	50.1
Subject 7	76.9	22.9	23.4	74.6	27.5	23.4
Subject 8	95.3	4.7	4.7	71.1	44.4	13.4
Subject 9	82.4	16.1	19.2	93.2	5.3	8.4
Subject 10	89.2	9.7	12.0	50.0	27.0	73.0
Mean(STD)	**86.1(7.3)**	**13.9(7.7)**	**13.9(7.5)**	**70.6(14.6)**	**22.3(13.1)**	**36.5(24.9)**

5. Conclusions and further research

Ever since it has been known that the brain activity of an individual is determined by a unique pattern of neural pathways, brain signals have emerged as a prominent biometric. In this paper, we proposed a novel EEG-based biometrics paradigm using self-face specific-representation in a human brain. The proposed method utilizes self-face and non-self-face images as stimuli to evoke electrical potentials. It activates a subject's own unique pattern of response to a pure face image, regardless of the will of the subject. Unlike previous EEG-based biometrics which used a resting state, motor imagery, or VEP, it is evidenced that the proposed stimulus paradigm generates unique subject-specific brain-wave patterns to self- and non-self-face images, which is in accordance with previous findings of psychological and neurophysiological studies. While our research was motivated from the face-related neurophysiological studies performed on Caucasians [22,24–26]. We could confirm that the same neurophysiological phenomenon is observed in our Korean dataset. From this fact, we believe that the proposed person authentication method can possibly be applied across ethnicities.

We also proposed a method of subject-specific channel and time interval selection using a pointwise biserial correlation coefficient and a statistical significance test. The selection of a time interval for each channel individually reflects the important feature of the time delay during visual processing in a human brain. It allows us to make a system immune to forgery since the selected channels and time interval for a specific client may not be consistent with those for imposters. In our experiment with 10 subjects, we confirmed that the proposed method resulted in high performance compared to previous methods of EEG-based person authentication.

Although the proposed EEG-based person authentication system recorded relatively lower performance compared to other widely used traits, namely, face, iris, and fingerprints, it is still meaningful as a biometric system due to its immunity to forgery and the impossibility of duplication. Also, unlike other biometrics, the proposed technique is even applicable for physically disabled persons whose brains are still working, such as persons with amyotrophic lateral sclerosis or locked in syndrome. Regrettably, there remains a problem in applying the EEG device to various real world scenarios due to its usability, but it is still better than other brain imaging techniques.

For this reason, in our future research we will integrate our system with other biometrics systems to improve usability and pattern analysis. We have a concern on the problem of ERP components' variation for a single subject. In this work, we performed experiments on the dataset collected over approximately three months. It will be meaningful to repeat the experiments after a year or so on a newly collected dataset to validate the effectiveness of the proposed method, and to perform the experiments using different images from the same subject.

Acknowledgments

This work was supported in part by the World Class University (WCU) Program through the National Research Foundation of Korea funded by the Ministry of Education, Science, and Technology, under Grant R31-10008 and in part by the Korea Science and Engineering Foundation (KOSEF) Grant funded by the Ministry of Education, Science, and Technology, under Grant 2012-005741.

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