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The affective facial recognition task: The influence of cognitive styles and exposure times ☆

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ABSTRACT

The main task of emotional facial recognition is to understand human emotion expression through the recognition of facial expressions, so as to achieve more effective communication and interpersonal communication. Therefore, facial recognition plays an important role in people's daily lives. In addition, the research of facial recognition is also helpful to understand the human perception processing mode, and promote the development of pattern recognition, cognitive science, neural network and other fields. With the development of cognitive science, facial recognition technology has been continuously improved, and emotional facial recognition tasks have received attention in the fields of pattern recognition and artificial intelligence, and have become a research hotspot. Among them, pattern recognition is a cognitive system applied to many fields. For the first time, we confirmed the effects of facial memory time, personal cognitive style, and emotions associated with the target face on facial recognition patterns. This study measured the impact of time, cognitive style, and emotional type of 62 qualified college students. The research results show that cognitive style and facial emotional content are of great significance for face pattern recognition. Specifically, students classified as "dependent" have achieved good results in face pattern recognition, and positive and negative strong emotional faces have left behind those who show neutral emotions. A deeper impression. Finally, an unusual phenomenon was discovered, which indicates that the shorter the time spent on the face of the memory, the higher the recognition score.

1. Introduction

Pattern recognition is a cognitive process that acquires information from previous stimuli and compares it with new information [1]. Face recognition is a daily form of pattern recognition that can be seen as a social activity. In the daily social activities of human beings, the expression and understanding of emotions play a vital role in interpersonal communication. The main task of emotional facial recognition is to understand human emotion expression through the recognition of facial expressions to achieve more effective communication and interpersonal communication. The human face is a unique organ of the human body. It contains a wealth of information such as emotion, race, gender, age, etc. The research and analysis of facial features provide a better solution for emotional facial recognition tasks. With the deepening of the research on emotional facial recognition, the human perception processing mode is easier to understand, and has made some progress in the fields of pattern recognition, cognitive science, and neural network. In recent years, face recognition has been favored by more and more people, and has been widely used in transportation, health and information security. Face recognition has become a research hotspot in the field of artificial intelligence.

In the field of facial recognition, many neuroscience studies report three main stages of facial recognition [2]. The first phase focuses on physical characteristics; the second phase focuses on the basic mechanisms of the cognitive system, which is used to reconstruct a person's identity from previous experience; that is, to provide a constructive period of signal with known People are similar. The last stage extracts the name associated with the target person. Thomas et al pointed out in the theory of facial recognition development that adults have a baseline system for facial recognition [3]; Bölte et al propose several general factors that can

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improve recognition, including attention concentration, deliberate task strategies and metacognition [4]. Developmental problems can be assessed by the relationship between facial recognition and ability. For example, Adolphs found that impaired social development in the autism spectrum is often accompanied by behavioral markers that tend to stay away from the face, as well as neuromarkers, which are characterized by decreased neurological activity in the spindle-shaped cerebral gyrus [5]. In the past 10 years, people have conducted in-depth research on the effects of time, individual cognitive style and target image characteristics. In terms of cognitive style research: Khan et al 's research shows that the reason for improving the long-term memory of cognitive scores is that participants can process more target images, so partially generated memories can enter long-term memory [6]; Lane et al studies have shown that people with dependent styles can convert original pictures into working memory, which is the main reason for obtaining better cognitive period scores [7]; Braver et al's research shows that these two cognitive ways The difference is due to the fact that participants of the dependency style tend to memorize facial features, while independent students usually extract features from the original image and tend to use their own markup system to remember [8]; Macrae and Lewis' research shows For independent cognitive style students, it is difficult to recall abstract information when they have to provide a description [9]. The complexity of recognition overwhelm their own marking system to remember the characteristics of the target face. Therefore, their facial stimulation recognition system is much more complicated than relying on the system used by students. In other words, students with independent cognitive skills need more practice to apply this ability to the real world; Happé et al's research found that students with dependent cognitive styles usually remember more about the target picture. Details such as the size of the mouth, the hairstyle of the target picture and the color of the skin [10]. In terms of exposure time: Klein et al found that the shorter the exposure time, the higher the recognition score [11]; Zhang et al pointed out that the memory load suppression effect caused by facial features is complex [12]. Subjects were asked to perform perceptual discrimination tasks on negative or neutral images, suggesting that high-intensity emotions significantly interfere with perceptual discrimination under conditions of low perceptual load and longer presentation time (men who are larger than dependent cognitive styles usually Remember more about late details) T pictures, such as the size of the mouth, the hairstyle of the target picture and the color of the skin; in the experiment of Florin et al., only 8 emotional faces need to be learned in each learning phase, and the perceived load is low. When the presentation time is increased to 1000 msec and 2000 msec, the subject learns 8 faces and then recognizes them one by one, so that the interval between learning and recognition is greatly increased to interfere with face recognition [13]. Neely pointed out that individual psychological processing differs due to different presentation times, while emotional images are controlled to be processed at greater than 400 msec [14]. Hermans et al's research shows that the presentation time is less than 300 msec, and the recognition rate is relatively stable, that is, the automation of emotional processing [15]. That is to say, because the picture is presented in this experiment for a long time, far exceeding the time of automatic processing, the memory traces are not strengthened and gradually weakened, resulting in the final return. Therefore, too much time may overload the participants' memory. In facial emotion research: Thomas et al found that pictures showing negative emotions (for example, sad faces) often leave a strong impression on participants compared to pictures showing neutral emotions [16]; González- Garrido et al.'s research shows that negative emotions trigger the most significant memory, providing further support for explaining the differences in image recognition patterns based on emotion types [17]. Second, Hur et al. found that bad memories are better than good memories. Better preserved [18]; Berger et al.'s research suggests that negative emotions often lead to more thoughts, that is, in image pattern recognition, negative emotion pictures attract more attention resources than positive emotion pictures. Participants are more likely to get more information from their internal systems than from positive emotional images [19]; Zhou et al. point out that in Chinese culture, people compare the impact of negative experiences to positive experiences [20]. This cognitive habit shifts to picture pattern recognition and predicts that participants will be more concerned with negative emotions associated with past uncomfortable experiences. Thus, between negative emotional pictures and positive emotional pictures, participants associate more information related to negative emotional descriptions than positive emotional descriptions; Chen et al.'s research suggests that people tend to report what they think Something worth sharing [21]. In facial recognition studies, meaningful performance of sadness and happy emotions is considered to be special compared to neutral emotions. Neutral emotions trigger less memory, and participants' descriptions of neutral emotions retain less information than meaningful emotions. In addition, Decety and Chamina pointed out that participants can also associate emotion-expressing faces with their own experience of enhancing memory [22]. However, for a picture of a happy mood or a sad mood, it is easier to associate a particular experience with the target facial features.

From the current research status, with the deepening of research in the field of emotional facial recognition, there are more and more research methods, and the fields involved are more and more extensive [28–31]. Although some research results have been achieved on the factors affecting the emotional facial recognition task, the existing research perspectives and methods need to be further improved, and few studies have simultaneously measured time, personal cognitive style and facial type. The underlying mechanism of influence, facial recognition patterns remains unclear. At present, most of the research methods of emotional facial recognition tasks use traditional behavioral research. This method draws conclusions by observing the respondents' responses to recognition tasks, and cannot understand the processing mode of human facial cognition in emotional facial recognition. In addition to the limitations of integration, there are limitations in the integration of other research methods. The research on the influencing factors of emotional facial recognition task mostly focuses on the change of face, that is, the influence of face inversion and blur on the facial recognition task. Changes in research task participants such as cognitive style, exposure time, etc. have little impact on recognition.

The main research methods of emotional facial recognition tasks include traditional behavioral research and cognitive neuroscience research methods. The traditional behavioral research method is mainly to conduct research and analysis by showing the face image to the participants and recording the reaction results. Cognitive neuroscience research includes techniques such as event-related potential (ERP), positron emission computed (PET), and functional magnetic resonance imaging (FMRI). ERP has the advantages of high temporal resolution and precise time positioning, and can better observe the processing mode of emotional facial recognition in human brain cognitive process. For example, Batty et al found that the latency and amplitude of N170 caused by different facial recognition processes were different, and positive emotions were earlier than N170 of negative emotions [23]; Balconi and Pozzoli et al. found that in the process of emotional facial recognition There is a N230 component in the back of the left brain [24]; Zhou Hongzhen and others conducted experiments through simple emotional facial images, and found that positive and neutral emotions are different in the frontal and occipital regions, negative emotions and neutral emotions are in Differences occurred in the central top zone, the right frontal zone, and the right occipital zone [25]; Jiang Changhao et al. found a significant positive difference based on the ERP waveforms in emotional facial recognition, and the results showed that the component was emotionally specific. Processing related [26]. From the application results of ERP in emotional facial recognition at home and abroad, this paper combines the traditional behavior research method with ERP technology to be applied to the influencing factors of emotional facial recognition tasks.

Many studies using picture facial recognition classify the influence of participants' cognitive styles, emotional content of pictures, and assigned picture recognition time. However, the main determinant of facial recognition remains to be detected. This study measures the main factors affecting facial pattern recognition by cross-evaluating cognitive patterns, time, and picture types. This study explored the effects of cognitive style, memory time and facial emotion types on face recognition based on adult fast automatic facial recognition, and measured the factors affecting the entire face recognition mode. This study explores two hypotheses:

(1) Cognitive style is a subjective factor that affects face recognition.
(2) Emotional type and exposure time are objective factors that affect face recognition.

The research results show that cognitive style and facial emotional content are of great significance for face pattern recognition. Among them, students who rely on cognitive methods achieve better results in face pattern recognition than students with independent cognitive methods. Pictures related to positive or negative emotions are more impressive than neutral emotions, and negative emotions have a greater impact. The results of the study show that the longer the exposure time, the lower the recognition score. The research results show that the cognitive mode and emotional content of the target image have more influence on the pattern recognition than the exposure time of the target image.

2. Proposed method

2.1. Face image preprocessing

Image preprocessing is the first step in pattern recognition. In the process of image acquisition, it will be affected by factors such as the degree of illumination and the performance of the acquisition device, so that the acquired image has problems such as insufficient contrast and noise. Moreover, the size and position of the face image collection in the overall image are difficult to determine. Therefore, this paper preprocesses the face image collected from the face sample database.

2.1.1. Face sample database

The sample data in the face sample database established in this paper is derived from the Chinese Affective Picture System (CAPS). This article uses a total of 216 face photos, half of which are male and half are female, with 72 photos in each emotional category (positive, neutral, and negative), as shown in Fig. 1. These pictures are clearly selected from the more than 2000 pictures with oriental characteristics, according to the clear and clear meaning of the content, without the words and as much as possible. Participants in each experimental treatment combination completed 2 blocks, each of which included 8 trials. For example, participants in a dependent group must complete nine experimental treatment combinations [emotions (pos, neu, and neg); duration of stimulation (500, 1000, and 2000 ms)] during the learning phase. There are 144 photos in this stage. In the identification phase, each block has 4 previously studied images and 4 new images, so there are a total of 72 images at this stage.

2.1.2. Image preprocessing method

(1) Grayscale

Face images are generally classified into color images and grayscale images. The pixels of the color image are composed of R (red), G (green), and B (blue) ternary colors, and different contents of R, G, and B constitute different colors. A grayscale image refers to an image that contains only luminance and does not con-

Fig. 1. Part of the face sample database picture.

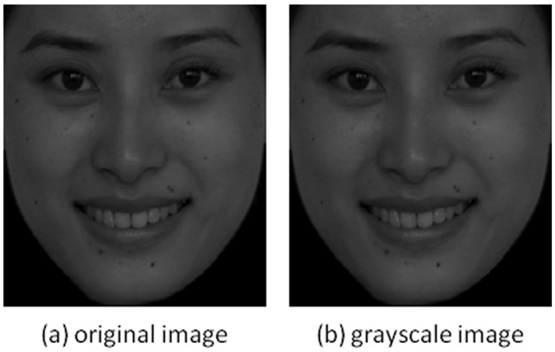

Fig. 2. Effect of grayscale processing.

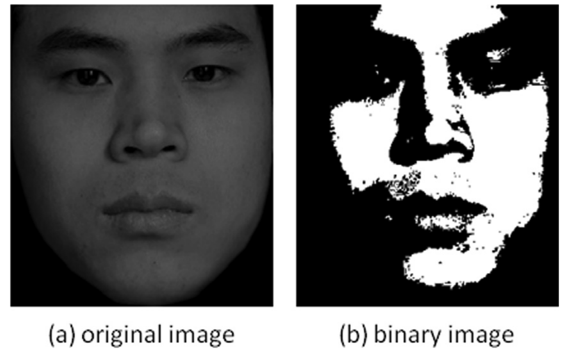

Fig. 3. Effect of binary processing.

tain color information. Grayscale is the process of making the R, G. B components of a color equal. There are three main types of common grayscale processing methods:

(1) Maximum method: Let the values of R, G, and B be equal to the maximum value, and the formula is as follows:

$$R = G = B = \max(R, G, B)$$

(2) Average method: Let the values of R, G, and B be equal to their average values, and the formula is as follows:

$$R = G = B = (R, G, B)/3$$

(3) Weighted average method: Let the values of R, G, and B be equal to the values obtained by mixing the colors in different proportions. The formula is as follows:

$$R = G = B = aR + bG + cB$$

where R, G, B represent three basic colors, respectively, a, b, and c represent the weights corresponding to the three colors, respectively. Grayscale with the maximum method yields a grayscale image with a very high brightness, while the average method yields a softer grayscale image. Therefore, the weighted average method is used to perform grayscale processing on the acquired image. The effect of grayscale processing is shown in Fig. 2.

(2) Binarization

The image after the grayscale image is linearly transformed by the gray histogram is still a multi-value image. A multi-value image is a monochrome image having a plurality of gray levels. A binary image is an image with only two gray levels in black and white. After binarizing the image, a binarized image with gray values of only 0 and 1 is obtained.

Let the grayscale distribution of the object in a grayscale image I (i,j) be in the interval [T1, T2], and the image after the threshold operation is the binary image B(i,j), the formula is as follows:

$$B(i,j) = \begin{cases} 1 & T1 \leqslant I(i,j) \leqslant T2 \\ 0 & \text{Other} \end{cases}$$

In the research of image processing, there are many methods of image binarization. Different image binarization methods have their own characteristics. Different binary segmentation effects are obtained for the same image processing. The quality of the binarization depends on the choice of threshold. Common binarization methods include local threshold method, global threshold method and dynamic threshold method. This paper uses the overall threshold method, and the effect of binarization is shown in Fig. 3.

(3) Energy normalization

The main task of energy normalization is to unify the samples of different modes by unifying the energy of each mode sample to unit energy. In addition, energy normalization can reduce the effects of illumination to a certain extent. In the actual face recognition problem, the illumination changes largely affect the performance of face recognition. For an $M \times N$ face image p(x, y). The energy definition formula of the image is as follows:

$$\| p \| = \left(\sum_{x=1}^{M} \sum_{y=1}^{N} p^2(x,y) \right)^{1/2}$$

After the energy is normalized, the image $\hat{p}(x,y)$ is:

$$\hat{p}(x,y) = \frac{p(x,y)}{\| p \|}$$

Energy normalization reduces the effect of linear light intensity on the recognition task.

(4) Smoothing and median filtering

Smoothing is the image processing method of the image, which takes a small area from the image centered on a certain pixel, and then uses the pixel value of the small area to perform a new operation to obtain the new value of the central pixel. Smoothing is usually achieved by convolution.

(a) Two-dimensional convolution method: from the continuity of the convolution function, there are linear system convolution, convolution of continuous functions, convolution of discrete functions. Divided from the dimension of the convolution function, one-dimensional convolution, two-dimensional convolution, multi-dimensional convolution, and so on. The face image pixel function is a discrete two-dimensional function. The definition of two-dimensional discrete convolution is as follows:

$$p(x,y) \otimes F(x,y) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} p(m,n) F(x-m, y-n), \begin{cases} x = 0, 1, \ldots, M-1 \\ y = 0, 1, \ldots, N-1 \end{cases}$$

In the formula, p(x, y) is the original image of the face, and F(x, y) is the smoothing operator of the action. $M \times N$ indicates a region where the action is smooth.

(b) Neighborhood average method: In the neighborhood averaging method, there are weighted smoothing operators and unweighted smoothing operators. Most of the current methods use weighted neighborhood averaging.

Let an image be p(x, y), the width and height are W and H, respectively, one point g(m,n), m < H,n < W, taking $d \times d$ centered on the point The size of the neighborhood, so that the weighting factor of the neighborhood is Q (m, n), then the weighted output g (x, y), the formula is as follows:

$$\hat{g}(m,n) = \frac{1}{d \times d} \sum_{x=m-k}^{m+k} \sum_{y=n-k}^{n+k} g(x,y)Q(m,n)$$

where k = d/2.

(c) After smoothing, most of the noise in the face is removed, but there may still be some isolated noise. The presence of these noises greatly affects the positioning effect, and it is necessary to remove these isolated noises as much as possible. In order to further remove these noises, a median filtering process is performed in this paper.

Median filtering is a nonlinear processing technique that suppresses image noise. In the one-dimensional case, the median filter is a window with an odd number of pixels. After processing, the gray value of the pixel located in the center of the window is replaced by the median of the odd-numbered pixel gray values in the window. The median filter does not affect the step function and the ramp function, thus protecting the image boundary, but suppressing pulses with a duration less than 1/2 of the window width, and thus may detract from some image detail. A two-dimensional median filter is the most commonly used filter. It is a neighborhood operation, similar to convolution, but instead of weighting the sum, it sorts the pixels in the neighborhood by grayscale and then selects the middle of the group as the output pixel value.

Suppose a 3×3 neighborhood is used for median filtering. The original image is p(x, y), where one point is g(m, n). This point is $\hat{g}(m,n)$ after median filtering. The formula is as follows:

$$\hat{g} = Med(g(m-i, n-j), -1 \leqslant i \leqslant 1, -1 \leqslant j \leqslant 1)$$

In the formula, Med() means taking the intermediate value. The median filtering result is shown in Fig. 4.

2.2. Cognitive style

2.2.1. Cognitive style related concepts

Cognitive style originated in the 1940s, but is not as widely known as learning theory. It originated from a narrow concept in the personality of cognitive psychology. More commonly, it is called "cognitive mode." In the field of cognitive style research, Richerd. Riding of the University of Birmingham in the United Kingdom, after doing a lot of research, proposed the definition of authority: cognitive style is considered to be the individual organization and representation of information Preference, habitual style Cognitive style determines how an individual reacts to different situations. It is an indicator of the characteristics of individual differences [27].

The "field" in the field independent/field-dependent cognitive style essentially refers to the environment, and the environment has a very important influence on people. It can be seen that the influence of field independent/field-dependent cognitive style on people is extremely important. Field independent cognitive styles prefer to actively recognize, perceive, and process information without external force; while field-dependent cognitive styles prefer to use external forces, which lacks autonomy compared to the former. In the process of perceptual sensation, the field independents can identify and find out what they want from the complex background environment, and can compare the relationship between the agile part and the whole. The field dependents are easily affected by the environment and are not good at Things are distinguished from the whole and are easily interfered by other factors. Field independent/field dependent cognitive style is an important indicator of individual personality traits.

(a) original image (b) filtered image

Fig. 4. Median filtering effect.

2.2.2. Cognitive style determination method

The commonly used cognitive styles are measured as follows:

(1) Bar box test: Immediately, the subject adjusts a tilt bar presented in the box to a vertical state under the condition of fixation. Individuals whose visual influence is greatly affected by environmental factors are dependent, and independent or less affected by environmental factors are independent. The early bar box test was done in the darkroom. Later, Altman designed the hand-held tester, which is more convenient to do. Based on this, it is improved to the bar frame instrument that we are currently common.
(2) Mosaic Graphic Test (EFT): The test pen is required to sketch a specific simple graphic embedded in a complex graphic. Field independents score higher than field dependents.
(3) Cognitive Style Graph Test (CSFT): CSFT is a standardized test. The reliability is 0.90 and the effective size is 0.49. This method was used in this study.

2.3. event-related potential analysis method

2.3.1. Event-related potential concept

ERP is a variability potential that is closely related to human brain activity and can induce brain electrical changes in human physical activity or mental activity. The event-related potential is different from the common evoked potential. The event-related potential reflects the change in the brain when the stimulus is generated. The common evoked point is a wide range of nerve-varying potentials for the stimulus itself, with no events. Brain potential specificity of the relevant potential. In 1965, Sutton proposed the concept of event-related potentials, providing a simpler and more effective way to understand brain function. After extensive research, he used a skull surface recording method, which measures many positions on the scalp. Specific points, record changes in potential differences induced by specific points in the psychological or physiological changes of the subjects to indirectly reflect changes in the brain's neurobioelectricity during cognitive processes. After many tests and studies, the events were determined. The change of related potentials is closely related to the individual cognitive process. Therefore, it is also said that event-related potentials can help to study the "window" of "snooping" individual psychological changes, and it is extremely important to explore changes in cognitive processes.

ERP as a special brain evoked potential mainly refers to a bioelectrical reaction that produces a detectable specific phase at a potential point when a specific stimulus is administered to a nerve. The particularity is that when measuring a certain component of EEG, it must correspond to a specific part, and each potential point has its own unique amplitude, latency and distribution, and the incubation period and the stimulus have a very close interaction relationship, often in immediately or during a specific time period when the stimulus is given. The analysis of event-related potentials is generally analyzed and compared from the frequency of occurrence of a certain time period or a certain potential point and the correlation between the leads of different parts of the scalp. Event-related potentials are characterized not only by the characteristics of the relevant indicators but also by the distribution of the scalp.

2.3.2. Event-related potential research indicators

The event-related potential research indicators mainly include two variables: amplitude and latency. In today's research, the term describing latency is generally defined by the length of time concept. It reflects the time course in which an individual performs cognitive processing on a stimulus, and is a measure of the speed of cognitive processing of the stimulus. The instantaneous judgment of the individual when the stimulus occurs, the extraction processing of the memory, and the cognitive ability recognition level are the time periods from the start of the stimulation to the completion of the cognitive processing of the stimulus. The amplitude is generally expressed in terms of the magnitude of the positive and negative wave values, which reflects the sum of the level of attention resources invested by the individual in the neural activity of a stimulus. It refers to the positive and negative potential changes from the start of stimulation to the event-related potential. Theoretically, the shorter the incubation period, the earlier the time course of stimulating the brain to perform cognitive processing; the larger the amplitude, the higher the level of neural activity caused by the stimulus, and the more attention resources are devoted to the stimulus. Therefore, in the study of event-related potentials, it is often from the perspective of analyzing the length of the incubation period and the magnitude of the amplitude of the amplitude to explore the relationship between an ERP component and the stimulus.

2.3.3. Event-related potential analysis process

In this paper, the collected raw EEG data is analyzed offline. The basic steps are as follows:

(1) EEG preview: preview the collected raw EEG data to eliminate the abnormal EEG signal.
(2) Lead screening: Select useful lead channels according to experimental requirements. Exclude M1, M2 here the four leads, M1 and CB2, only process the remaining 60 leads.
(3) Reset reference electrode: In this experiment, when the data is collected, the reference electrode is placed on the top of the head. Offline to average reference electrode.
(4) Filtering: here a Chebyshev low-pass filter with a cutoff frequency of 30 Hz (4th order IIR)Filter) Filters the data, which reduces power line interference and electro-muscle artifacts with frequencies greater than 30 Hz.
(5) EEG segmentation: In order to comprehensively analyze the signal, the end truncation time generally includes the effective time, and in order to perform baseline correction processing on the data, the initial deadline is generally before the stimulus is presented. In this experiment, the time to effectively view the face image is 300 ms, so the data segment selected for interception is 50 ms before the stimulus presentation starts and 500 ms after the stimulus presentation.

3. Experiments

3.1. Experimental design

The experiment used 2 (cognitive mode: independent / dependent) × 3 (exposure time: 500 msec / 1000 msec / 2000 msec) × 3 (facial emotion: positive / neutral / negative) mixed experimental design, cognitive mode in the subject variable The exposure time and face are within the subject variable. The dependent variable is the recognition rate of facial emotions.

3.2. Experimental participants

A total of 99 healthy college students were randomly selected to participate in the study. Prior to the experiment, all participants were subject to Cognitive Style Mapping Test (CSFT), which divided participants into dependent or independent cognitive styles. The test results showed that 64 patients had independent cognitive styles (mean = 19.45) and 35 patients had independent cognitive styles (mean = 9.13). Due to the scheduling of the subjects, 82 students (51 with cognitive style and 31 with independent cognitive style) completed a series of further tests. We randomly selected 31 students from a larger independent group. To balance the number of participants in each group. The mean age of the dependent group was 20.25 years (standard deviation = 1.76; range 19–22), and the mean age of the independent group was 20.38 years (standard deviation = 1.58; range 19–22).

3.3. Experimental procedure

All experiments were performed on e-prime 2.0 on a laptop with the Windows 10 operating system. The study measured the cognitive style, exposure time, and effectiveness of emotional content. All experiments lasted approximately 40 min. After the end of each experimental group, all participants rested for 3 min. We will take the example of a dependent cognitive approach participant at 500 ms. The experimental structure is shown in Fig. 5.

(1) Practice phase: The purpose is to familiarize participants with the experimental process. The results of this phase are not counted in the total score.

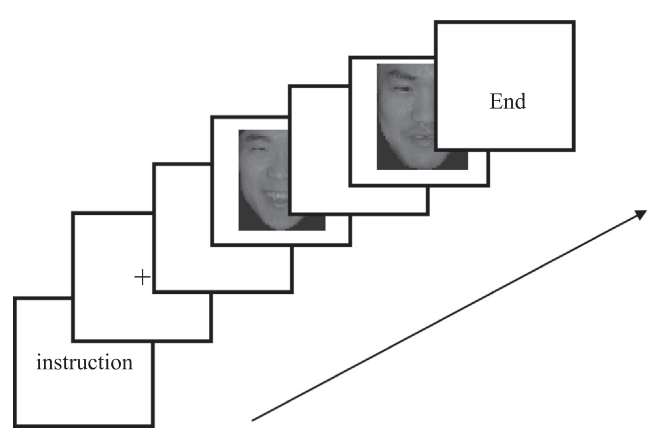

Fig. 5. Experimental figure.

Table 1
Descriptive analysis.

Cognitive style	Exposure time	Emotion types	*Mean* (%)	*SD*
Independent	500 msec	Neutral	0.41	0.11
		Positive	0.31	0.10
		Negative	0.61	0.10
	1000 msec	Neutral	0.38	0.06
		Positive	0.20	0.16
		Negative	0.51	0.10
	2000 msec	Neutral	0.37	0.14
		Positive	0.22	0.15
		Negative	0.54	0.14
Dependent	500 msec	Neutral	0.52	0.10
		Positive	0.46	0.14
		Negative	0.65	0.10
	1000 msec	Neutral	0.50	0.12
		Positive	0.38	0.09
		Negative	0.62	0.12
	2000 msec	Neutral	0.51	0.13
		Positive	0.44	0.15
		Negative	0.62	0.16

Table 2
Repeated measures of the effect on picture recognition pattern.

Check list	*SS*	*df*	*MS*	*F*
Cognitive style	2.339	1	2.339	78.482***
Memory time	0.356	2	0.178	9.228***
Emotion type	6.149	2	3.075	23.850***
Cognitive style × Emotion type	0.231	2	0.116	8.725***
Memory time × Emotion type	0.074	4	0.019	1.707
Cognitive style × Memory time	0.050	2	0.025	1.290
Emotion type × Memory time × Cognitive style	0.026	4	0.006	0.596

Note: $^{***}p < 0.001$.

(2) Learning phase: First, a red "+" (exposure time 500 ms) is displayed in the center of the computer screen, and then a facial emotion picture (as a stimulus) is displayed. In one block, a stimulus picture is displayed, for a total of 8 pictures. Between the pictures, there is a blank display that is 300 ms long.
(3) Recognition stage: At this stage, 8 pictures are displayed as target stimuli, 4 of which have been displayed, 4 are not displayed, and the next recognition picture appears only when the participant presses the response key. If the participant has already seen the photo, he/she should press "J", otherwise press the "M" button. The correct answerer gets 1 point, and the wrong answerer gets 0 point.

4. Results and discussions

Behavioral data was processed using SPSS 24.0 software. The correct response was analyzed by 3-factor repeated measures analysis of variance. If the difference is significant, the LSD multiple comparison analysis (LSD post hoc test) is used.

Table 1 shows that participants identified as dependent cognitive types received higher cognitive scores than independent groups. Second, the longer the memory time, the lower the image recognition score. Third, negative emotions have a greater impact on memory than neutral ones. A simple effect analysis of behavioral data showed that the cognitive style group had significant differences in positive and neutral emotions ($F = 20.57$, $P < 0.001$; $F = 18.42$, $P < 0.001$). However, in terms of negative emotions, the differences between cognitive style groups were not significant ($F = 5.33$, $P > 0.05$). In addition, this paper also explores the group differences between positive and neutral emotions. The results show that the cognitive scores of the dependent cognitive style group are higher than the independent cognitive style group.

Table 2 shows the main effects of cognitive style, memory time, and picture sentiment type ($P < 0.001$). The interaction between cognitive style and emotional type on image recognition was significant ($P < 0.001$). Other interactions between cognitive style, memory time, and emotional type were not significant ($P > 0.05$). In the LSD analysis, the recognition time was significantly different between 500 ms and 1000 ms ($p < 0.01$), but there was no significant difference between 1000 ms and 2000 ms ($p > 0.05$). For the types of emotions found in LSD analysis, there was a significant difference between each emotion type and other emotion types ($P < 0.05$). The cognitive level of neutral emotion map and positive emotion map was significantly different ($P < 0.05$), and the cognitive level of negative emotion and neutral emotion was significantly different ($P < 0.01$).

After the EEG data is recorded and collected using Curry7 software, the detection and screening of artifacts are automatically completed by software. If the amplitude exceeds 0-40uV, the superposition will be eliminated. Then, the repeated exposure analysis of variance (ANOVAs) method was used to analyze the exposure time, short (500, 1000 msec).

Tables 3 and 4 show the specific values of latency and amplitude for short, long exposure times under PO8 or PO7 leads. When the *t* test was used to test the PO6 or PO7 lead for a significant difference in the N170 amplitude of the short exposure time and long time, there was no significant situation. However, when comparing the left and right hemispheres, that is, the pairwise comparison between the PO8 and PO7 leads, the amplitude at the time of exposure time of 500 ms ($p = 0.017 < 0.05$) and the amplitude of the exposure time of 1000 ms ($p = 0.012 < 0.05$) was significantly greater in the left hemisphere than in the right hemisphere. When

Table 3
Magnitude and latency of N170 components at 500 ms exposure time.

	Incubation period (ms)	Amplitude (μV)
PO8	153.91	−2.21
PO7	155.20	−3.32

Table 4
Magnitude and latency of N170 components at 1000 ms exposure time.

	Incubation period (ms)	Amplitude (μV)
PO8	158.95	−2.32
PO7	160.01	−3.20

the magnitude of N170 was studied irrespective of the lead, no significant differences were found.

5. Conclusions

With the continuous development of emotional facial recognition, there are more and more research methods on the influencing factors of emotional facial recognition, and the fields involved are more and more extensive. However, existing research perspectives and methods need to be further improved, and few studies have simultaneously measured the effects of time, personal cognitive style and facial type. The underlying mechanism of facial recognition patterns remains unclear. Therefore, this paper measures the main factors affecting facial pattern recognition ability by cross-evaluating cognitive style, time and picture type. This study explored the effects of cognitive style, memory time and facial emotion types on face recognition based on adult fast automatic facial recognition, and measured the factors affecting the entire face recognition mode. Studies have shown that in pattern recognition of pictures, students who rely on styles perform better than students in independent styles. The longer the target image is exposed, the lower the recognition score. Pictures related to positive or negative emotions are more impressive than neutral emotions, and negative emotions have a greater impact. Research shows that the cognitive mode and emotional content of the target image have more influence on the pattern recognition than the exposure time of the target image.

Declaration of Competing Interest

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References

[1] J. Huang, The FERET database and evaluation procedure for face recognition[J], Image Vis. Comput. J. 16 (5) (1998) 295–306.
[2] P.J. Phillips, H. Moon, S.A. Rizvi, et al., The FERET evaluation methodology for face-recognition algorithms[J], IEEE Trans. Pattern Anal. Mach. Intell. 22 (10) (2000) 1090–1104.
[3] L.A. Thomas, M.D.D. Bellis, R. Graham, et al., Development of emotional facial recognition in late childhood and adolescence[J], Dev. Sci. 10 (5) (2010) 547–558.
[4] D. Hubl, S. Bölte, S. Feineis-Matthews, et al., Differences in primary visual areas for face recognition between autistics and healthy controls[J], Neuroimage 13 (6) (2001) 1058.
[5] R. Adolphs, S. Baron-Cohen, D. Tranel, Impaired recognition of social emotions following amygdala damage[J], J. Cognit. Neurosci. 14 (8) (2002) 1264–1274.
[6] R.A. Khan, A. Meyer, H. Konik, et al., Framework for reliable, real-time facial expression recognition for low resolution images[J], Pattern Recogn. Lett. 34 (10) (2013) 1159–1168.
[7] R.D. Lane, L. Sechrest, R. Riedel, et al., Pervasive emotion recognition deficit common to alexithymia and the repressive coping style[J], Psychosom. Med. 62 (4) (2000) 492–501.
[8] T.S. Braver, J.R. Gray, G.C. Burgess, Explaining the many varieties of working memory variation: dual mechanisms of cognitive control [J], Var. Work. Memory (2007) 76–106.
[9] C.N. Macrae, H.L. Lewis, Do I know you? Processing orientation and face recognition[J], Psychol. Sci. 13 (2) (2002) 194–196.
[10] Francesca Happé, U. Frith, The weak coherence account: detail-focused cognitive style in autism spectrum disorders[J], J. Autism Dev. Disord. 36 (1) (2006) 5–25.
[11] R.M. Klein, A.D. Castel, J. Pratt, The effects of memory load on the time course of inhibition of return[J], Psychon. Bull. Rev. 13 (2) (2006) 294.
[12] Y. Zhang, M. Zhang, Spatial working memory load impairs manual but not saccadic inhibition of return[J], Vision Res. 51 (1) (2011) 147–153.
[13] D. Florin, A.D. Iordan, K. James, et al., Neural correlates of opposing effects of emotional distraction on working memory and episodic memory: an event-related fMRI investigation[J], Front. Psychol. 4 (2013).
[14] James H. Neely, Semantic priming and retrieval from lexical memory: Roles of inhibitionless spreading activation and limited-capacity attention.[J], J. Exp. Psychol. Gen. 106 (3) (1977) 226–254.
[15] L.A. Thomas, M.D. De Bellis, R. Graham, et al., Development of emotional facial recognition in late childhood and adolescence[J], Dev. Sci. 10 (5) (2010) 547–558.
[16] D. Hermans, J.D. Houwer, P. Eelen, The affective priming effect: Automatic activation of evaluative information in memory[J], Cogn. Emot. 8 (6) (1994) 515–533.
[17] Andrés Antonio González-Garrido, Adriana Liset López-Franco, Fabiola Reveca Gómez-Velázquez, et al., Emotional content of stimuli improves visuospatial working memory[J], Neurosci. Lett. 585 (2015) 43–47.
[18] J. Hur, A.D. Iordan, F. Dolcos, et al., Emotional influences on perception and working memory[J], Cogn. Emot. (2016) 1–9.
[19] C. Berger, A.K. Erbe, I. Ehlers, et al., Effects of task-irrelevant emotional stimuli on working memory processes in mild cognitive impairment[J], J. Alzheimers Disease Jad 44 (2) (2015) 439–453.
[20] Q. Zhou, Y. Wang, X. Deng, et al., Relations of parenting and temperament to Chinese children's experience of negative life events, coping efficacy, and externalizing problems.[J], Child Dev. 79 (3) (2010) 493–513.
[21] C. Bai, J.N. Chen, L. Huang, K. Kpalma, S. Chen, Saliency-based multi-feature modeling for semantic image retrieval, J. Vis. Commun. Image Represent. 50 (2018) 199–204.
[22] O. Chen, S. Kalyuga, J. Sweller, The expertise reversal effect is a variant of the more general element interactivity effect[J], Edu. Psychol. Rev. 29 (2016) 1–13.
[23] J. Decety, T. Chaminade, When the self represents the other: a new cognitive neuroscience view on psychological identification[J], Conscious. Cogn. 12 (4) (2004) 577–596.
[24] M. Batty, M.J. Taylor, Early processing of the six basic facial emotional expressions.[J], Brain Res. Cognitive Brain Res. 17 (3) (2003) 613–620.
[25] M. Balconi, U. Pozzoli, Face-selective processing and the effect of pleasant and unpleasant emotional expressions on ERP correlates[J], Int. J. Psychophysiol. 49 (1) (2003).
[26] S.P. Rana, M. Dey, P. Siarry, Boosting content based image retrieval performance through integration of parametric & nonparametric approaches, J. Vis. Commun. Image Represent. 58 (2019) 205–219.
[27] Zhou Hongzhen, Li Yajie, Zhou Shu, Lu Xuesong, Luo Yifeng, Research and application of event-related potentials for facial expression, processing[J]. 25 (8) (2005) 921–925.
[28] Jiang Changhao, Zhao Lun, Guo Dejun et al. Emotional effects and potency effects of face processing Tian. Chinese J Clin Psychol Zoos, 16 (3), 237–239.
[29] He Wen, Progress in cognitive style research [J], Psychol. Sci. 24 (5) (2001) 631–632.
[30] R. Pramanik, S. Bag, Shape decomposition-based handwritten compound character recognition for bangla ocr, J. Vis. Commun. Image Represent. 50 (2018) 123–134.
[31] I. Bezzine, M. Kaaniche, S. Boudjit, A. Beghdadi, Sparse optimization of non separable vector lifting scheme for stereo image coding, J. Vis. Commun. Image Represent. 57 (2018) 283–293.

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