Emotional experience evaluation method of interaction task based on EEG technology

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Abstract: In past studies, the emotional experience of interaction task was quantified mainly by the subjective evaluation. This method is susceptible to subjective factor, which can cause the deviation of result. To solve this problem, an emotional experience evaluation method of interaction task based on objective Electroencephalograph(EEG) technology was proposed. Supported by the theory of cognitive neuroscience and EEG, the same family of products with different interaction processes were selected as a sample of experiment, and interactive tasks were set. Then the emotional experience evaluation experiment of interaction task was conducted to obtain objective EEG physiological information. Based on the Power Spectral Density analysis(PSD) and the event-related synchronization/desynchronization theory, characteristic values were calculated. Next, Correlation between the EEG characteristic value and the emotional experience of interactive tasks was judged by Pearson Correlation Coefficient. Finally, the partial least squares regression(PLS) was selected to construct the calculation model. Smartphones were used as the interaction case, and the model’s performance was verified. The results showed that the proposed calculation model could achieve the similar evaluation effect as the subjective evaluation, and the deviation was smaller.

1. Introduction

In the research of human-computer interaction, the emotional experience of product interaction system is one of the priorities. Researchers in neuroscience, psychology, and cognitive science had shown that human emotional responses could cause electrophysiological changes in the brain[1]. Therefore, to get user's Electroencephalograph(EEG) signal is an effective way to study the emotional experience of the product interaction system.

In the related research on emotional experience of interaction systems, Yang et al.[2] used the category hierarchy method to decompose the design project of the interface in the interaction task. And a mapping model between the affective image and design project was established to effectively guide the design of the interaction task interface. Lin[3] studied the emotional state of the car driving operation. Then an emotion detection method based on driver characteristics and vehicle running state was proposed. These studies mainly used subjective evaluation to quantify the emotional experience of the interaction system. The research based on this method has the characteristics of simple operation and high efficiency, but it is easy to be affected by subjective factor and lead to deviation of evaluation results[4].

In the EEG study, the EEG produced by the left and right frontal lobe is directly related to the emotional state[5]. The high energy response of the left frontal lobe represents positive feedback, while the high energy response of the right frontal lobe represents negative feedback[6]. The Power Spectral
Density (PSD) of five common EEG of α, β, θ, δ, and γ has been used to evaluate emotional states [7]. The PSD of the α wave is related to the inactive state of the brain and the positive valence state of the emotion. And the smaller the PSD, the more active is the brain [8]. Therefore, this study uses EEG measurement technology as a key means to quantify the emotional experience of interaction tasks, and constructs the calculation model based on EEG. This method solved the problem of subjective decision-making by designers when conceiving product prototypes and evaluating interaction design schemes, and provided objective user knowledge and scientific basis for designing product interaction prototypes that met the user's emotional experience. We took smartphones as examples to verify the effect of the interaction task emotional experience calculation model.

2. Construction of an emotional experience evaluation method of interaction task based on EEG technology

Common interaction tasks are selected based on the characteristics of the product interaction system. Products with the same function and different interaction processes were chose as samples in emotional experience evaluation experiment. The set of experimental subjects is set as \( B = \{b_1, b_2, b_3, \ldots, b_m\} \), where \( m \) is the number of subjects. And the set of product samples is \( C = \{c_1, c_2, c_3, \ldots, c_n\} \), where \( n \) represents the number of product samples. Subjective evaluation of interaction tasks usually includes six aspects: pleasure, autonomy, fluency, responsiveness, immersion, and overall functionality [9]. This study chose pleasure and immersion as the evaluation object of interaction emotional experience.

The experiment is to obtain the EEG data of the subject during the interaction task. The experimental steps are as follows: First, Subjects need to sit for 60 seconds and record EEG data in relaxed state. Then, the task guidance appears on the screen, and next the interaction task is performed. After completing all the interaction tasks of one product sample, the emotional experience of this product were evaluated by Subjects. Then subject experiments with another product sample after a little rest. The experimental flow of one product sample is shown in Figure 1.

![Figure 1. Emotional cognitive experiment flow of interaction tasks based on EEG.](image)

If the emotional experience score of the \( m \)-th subject \( (B_m) \) on the \( n \)-th product sample \( (C_n) \) is \( D \), the average score of all subjects on the \( n \)-th product sample can be expressed as Equation (1), where \( m = 1, 2, 3, \ldots, M \).

\[
y_m(C_n, D) = \frac{1}{M} \sum_{m=1}^{M} y(B_m, C_n, D)
\] (1)

The EEG equipment that the subject is wearing will record the EEG data during the interaction task. If the EEG data of the \( m \)-th subject \( (B_m) \) on the \( n \)-th product sample \( (C_n) \) is \( E_p \) and \( p \) is the number of EEG indexes. The average value of each EEG index of the \( n \)-th product sample used by all of the subjects can be expressed as Equation (2), where \( m = 1, 2, 3, \ldots, M \).

\[
y_m(C_n, E_p) = \frac{1}{M} \sum_{m=1}^{M} y(B_m, C_n, E_p)
\] (2)

This study will obtain the PSD of α waves (electrodes AF3, AF4, F3, F4, F7 and F8) in the frontal lobe of the subjects as physiological indicators of emotional response. There may be differences in α waves generated between subjects. In order to actually respond to the degree of α activation, the Equation (3) is used to calculate the characteristic value of EEG indexes, which is based on the theory of Event-related EEG synchronization and desynchronization [10].

\[
y_m(C_n, E_p) = \frac{1}{M} \sum_{m=1}^{M} y(B_m, C_n, E_p)
\]
Where \(F\) represents the characteristic value of the \(\alpha\) wave, and \(A\) and \(R\) are the PSD of the \(\alpha\) wave in the task phase and the rest phase, respectively.

When the screened EEG index \(E_p(\theta)\) is converted into formula \(\theta(E_p)\), the screened EEG index expression is as follows in Equation (4):

\[
E_p^\theta = \theta\left(\frac{1}{M} \sum_{m=1}^{M} y(B_m, C_n, E_p)\right)
\]

To predict the emotional experience score of the interaction task in product sample through the EEG indexes, an emotional experience calculation model of interaction tasks based on EEG is established. The emotional experience score is taken as the dependent variable \(y\), and the EEG indexes are the independent variables \(x\). Then the theoretical model of experience evaluation can be described as equation (5):

\[
Q = f[E_p^\theta, y_m(C_n, D)]
\]

where \(Q\) is the quantitative value of the interaction task emotional experience. \(f\) is the data-mining technology of the emotional experience calculation model. And \(E_p^\theta\) and \(y_m(C_n, D)\) represent the characteristic value of EEG indexes and the emotional experience score, respectively.

3. Method Verification: Smartphone Case Study

Because of the interaction tasks are simple and interaction processes are diverse, the smartphone is used as the experimental sample.

3.1. The emotional experience evaluation experiment of interaction tasks based on EEG

3.1.1. Objective

Get the EEG data of the subjects during the interaction task of the smartphone.

3.1.2. Subjects

Fifteen industrial design students participated in the experiment. The subjects’ ages ranged from 20–26 years old and averaged 24.323 years. All of the subjects were confirmed to be right-handed, to avoid individual differences in changes in the left and right brain hemispheres[11].

3.1.3. Experimental Samples

Four common smartphones with operating systems of iOS, MIUI, EMUI, and Smartisam OS were used as experimental samples. For the built-in program in the smartphone, three tasks were selected as the experiment task, the common function of to find the destination in the map, to download APP in the appstore, and to input the specified text in the notes were selected.

3.1.4. Experimental Equipment

Smartphone: To avoid the impact of product appearance, smartphones with the same screen size, appearance, colour and other factors were used as the experimental sample. After focus group discussion, iphone 7 Plus, Xiaomi Note 3, Huawei P10 Plus and Jianguo Pro four smartphones were selected. Each smartphone’s body was black, the screen size was 5.5 inches, and the appearance of the four smartphone is shown in Figure 2.
Figure 2. The appearance of four smartphones.

**EEG equipment:** The EEG hardware used in the experiment was the Emotiv EPOC+ wireless head-mounted EEG device with 14 channels. Sample rate is 124 Hz per second. The electrode positions were AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 (see Figure 3). In addition, CMS and DRL were used as reference electrodes.

Figure 3. The electrode positions.

**Experimental platform:** Two computers were required in this experiment, task computer with E-prime program and EEG computer connected to Emotiv EPOC+. The task computer was connected to the EEG computer through a serial cable and sends the Mark during the experiment. The Mark will mark the time point in the EEG data as an experimental event. The experimental platform is shown in Figure 4.

3.1.5. **Experimental Process**

The specific experimental process is as follows: First, The experimental instruction was displayed; Next, the subjects were asked to calm their mind and record the EEG for 60 seconds of rest. Then, jump to the description page of the first experiment task. Hit the space bar to start the task; After completing the task, press the space bar to go to the next task description page. 3 tasks of one smartphone will be arranged as a group. After one group was completed, the subjects needed to score 1~5 points on the overall emotional experience of this smartphone through the keyboard.
The duration of each task for each phone will last 2 to 3 minutes. Together with the preparation time, it took about 35 minutes for each subject to complete the experiment. The experimental flow is shown in Figure 1.

3.2. Data processing

3.2.1. Subjective evaluation

Table 1 shows the subjective evaluation results of the interaction task emotional experience. The evaluation contents were pleasure and immersion, with a score of 5 points.

| Content | Smartphone | N | Mean(M) | Standard deviation(SD) | Standard error |
|---------|------------|---|---------|-------------------------|---------------|
| pleasure | 1 | 12 | 4.13 | 0.34 | 0.21 |
| | 2 | 12 | 3.86 | 0.43 | 0.23 |
| | 3 | 12 | 3.23 | 0.68 | 0.35 |
| | 4 | 12 | 3.77 | 1.02 | 0.19 |
| immersion | 1 | 12 | 3.84 | 0.69 | 0.19 |
| | 2 | 12 | 3.57 | 0.43 | 0.26 |
| | 3 | 12 | 2.84 | 0.85 | 0.34 |
| | 4 | 12 | 3.68 | 0.46 | 0.37 |

3.2.2. EEG data
First, EEGLAB 14.1.2b was used to preprocess EEG data. The main steps included channel position importing, event value reading, reference electrode setting, band-pass filtering, EEG previewing, artifact removal, EEG segmentation, baseline correction, and noise components removal. Next, the PSD values of $\alpha$ from the electrodes AF3, AF4, F3, F4, F7 and F8 were extracted, and the result is shown in Table 3. It can be found that the relative $\alpha$ wave high energy of each electrode is at a higher level during the rest phase. It is generally reduced during the task phase, and the inactive state appears, indicating that a positive emotional state has occurred.

| Task phase | AF4 | AF3 | F4 | F3 | F8 | F7 |
|-----------|-----|-----|----|----|----|----|
| Rest phase | 0.29±0.18 | 0.28±0.19 | 0.27±0.17 | 0.29±0.18 | 0.28±0.16 | 0.29±0.15 |
| Smartphone1 | 0.15±0.08 | 0.14±0.09 | 0.14±0.05 | 0.14±0.04 | 0.14±0.08 | 0.13±0.07 |
| Smartphone2 | 0.13±0.07 | 0.15±0.04 | 0.13±0.05 | 0.14±0.06 | 0.13±0.06 | 0.14±0.04 |
| Smartphone3 | 0.14±0.06 | 0.11±0.07 | 0.12±0.07 | 0.11±0.08 | 0.12±0.07 | 0.12±0.04 |
| Smartphone4 | 0.12±0.08 | 0.13±0.06 | 0.11±0.06 | 0.13±0.09 | 0.13±0.07 | 0.13±0.02 |

The characteristic values of EEG indexes of the $\alpha$ wave were calculated by the Equation (3) in order to effectively reflect the activation degree of the brain. After calculation, the EEG characteristic values as shown in Table 3 were obtained. These characteristic values would be used as EEG indexes to establish an Emotional experience calculation model of interaction tasks.

| AF4 | AF3 | F4 | F3 | F8 | F7 |
|-----|-----|----|----|----|----|
| Smartphone1 | 0.483 | 0.500 | 0.481 | 0.517 | 0.500 | 0.552 |
| Smartphone2 | 0.552 | 0.464 | 0.519 | 0.516 | 0.536 | 0.517 |
| Smartphone3 | 0.517 | 0.607 | 0.556 | 0.621 | 0.571 | 0.586 |
| Smartphone4 | 0.586 | 0.535 | 0.593 | 0.552 | 0.536 | 0.552 |
3.3. Construction of emotional experience evaluation model based on smartphone interactive task

3.3.1. Determination of independent variable and dependent variable
Between 6 sets of α characteristic values and 2 sets of interaction task emotional experience mean values, The correlation analysis was used to gain pearson correlation coefficient(see Table 4). The absolute value of the correlation coefficient between the emotional experience mean values and the α characteristic value approaches 1, indicating that there is a linear relationship.

**Independent variable:** α characteristic values of the electrodes AF4, AF3, F4, F3, F8 and F7 in the frontal area of brain.

**Dependent variable:** The mean value of the emotional experience of the interaction task: pleasant and immersive.

|       | AF4  | AF3  | F4  | F3  | F8  | F7  | Pleasure | Immersion |
|-------|------|------|-----|-----|-----|-----|----------|-----------|
| AF4   | 1    | -0.086 | 0.798 | -0.005 | 0.321 | -0.322 | -0.149 | 0.077     |
| AF3   | -0.086 | 1    | 0.524 | 0.969 | 0.711 | 0.955 | -0.849 | -0.803    |
| F4    | 0.798 | 0.524 | 1   | 0.551 | 0.640 | 0.314 | -0.587 | -0.356    |
| F3    | -0.005 | 0.969 | 0.551 | 1   | 0.858 | 0.866 | -0.953 | -0.917    |
| F8    | 0.321 | 0.711 | 0.640 | 0.858 | 1   | 0.486 | -0.971 | -0.919    |
| F7    | -0.322 | 0.955 | 0.314 | 0.866 | 1   | 0.486 | -0.675 | -0.666    |
| Pleasure | -0.149 | -0.849 | -0.587 | -0.953 | -0.971 | -0.675 | 1   | 0.965     |
| Immersion | 0.077 | -0.803 | -0.356 | -0.917 | -0.919 | -0.666 | 0.965 | 1         |

3.3.2. Construction of multiple linear regression model
In table 4, the absolute value of the correlation coefficient between each α characteristic value approaches 1, indicating that there is a correlation between data. Therefore, the partial least squares regression(PLS) was used to establish the mathematical model, which could solve the adverse effects from the multiple correlation of variables[12]. The mean value of pleasure and immersion was the dependent variable Y. The α characteristic value was used as independent variables X. And the regression coefficients were obtained by PLS.

Two multiple linear regression models were obtained as shown in Equations (6) and (7).

**Pleasure:**

\[
Y_1 = 0.231x_{a,AF4} - 0.742x_{a,AF3} + 0.362x_{a,F4} - 2.640x_{a,F3} - 8.500x_{a,F8} + 0.658x_{a,F7} + 9.467
\]

(6)

**Immersion:**

\[
Y_2 = 1.735x_{a,AF4} - 0.599x_{a,AF3} + 2.108x_{a,F4} - 3.454x_{a,F3} - 12.027x_{a,F8} + 1.768x_{a,F7} + 9.111
\]

(7)

3.4. Model verification
To verify the evaluation effect of the model, reschedule the interaction task experiment of 4 smartphones. Subjective evaluation values and α characteristic values from each subjects were obtained. Bring each characteristic values into the Equations (6) and (7) to get the model calculation value. The mean(M) and standard deviation(SD) of each kind of evaluation value from 10 subjects were calculated.

The paired sample t test was performed between the subjective evaluation mean values and the model evaluation mean values. According to the significance level of t test results, the critical t value was 2.776. The mean of each evaluation value and the paired sample t-test result are shown in Table 6. The range of each evaluation value are 1 to 5 points. According to the table 6, the absolute value of t value is less than 2.776, indicating that there is no significant difference between the model calculation value and the subjective evaluation value. The practicability of the model is proved, and it has the effect similar to the subjective evaluation value.
The SD of each evaluation value are shown in Table 6. SD reflects the dispersion degree of the data. The SD of the subjective evaluation values in the table is generally larger than the SD of the model evaluation values. It is indicated that the deviation of the model evaluation value is smaller.

Table 5. The mean of each evaluation value and t values of paired samples t test t values.

| Evaluation Value | Sample1 | Sample2 | Sample3 | Sample4 | t value | Critical Value |
|------------------|---------|---------|---------|---------|---------|----------------|
| Immersion        |         |         |         |         |         |                |
| subjective       | 3.68    | 4.31    | 3.65    | 3.75    | 0.123   | 2.776          |
| model            | 3.74    | 4.23    | 3.72    | 3.68    |         |                |
| Pleasure         |         |         |         |         |         |                |
| subjective       | 4.21    | 3.91    | 3.86    | 3.78    | -0.420  |                |
| model            | 4.17    | 3.89    | 3.92    | 3.82    |         |                |

Table 6. The standard deviation of each evaluation value.

| Evaluation Value | Sample1 | Sample2 | Sample3 | Sample4 |
|------------------|---------|---------|---------|---------|
| Immersion        |         |         |         |         |
| subjective       | 0.510   | 0.311   | 0.602   | 0.842   |
| model            | 0.159   | 0.185   | 0.269   | 0.245   |
| Pleasure         |         |         |         |         |
| subjective       | 0.311   | 0.481   | 0.301   | 0.334   |
| model            | 0.159   | 0.215   | 0.196   | 0.371   |

4. Conclusion

This study proposes an emotional experience evaluation model of interaction task based on brain electrophysiological indexes. The research shows that the evaluation model based on physiological signal can achieve the similar evaluation effect with the psychological cognition-based evaluation method, and the deviation of the evaluation results is smaller. This method circumvents the uncertainty that may be caused by subjective evaluations, and provides product decision makers or designers objective user data support when selecting product interaction schemes for specific emotional attributes.

This study discusses the impact of EEG indexes on the emotional experience of product interaction tasks. However, the human body also has other physiological indexes such as eye movement, skin electricity, pulse, etc. Whether these indexes have an impact on the emotional experience of product interaction tasks needs further study. In addition, research on the triggering factors of each index will also help to directly relate physiological changes and design changes, and more effectively guide the design of product interaction schemes.

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