Brain responses in evaluating feedback stimuli with a social dimension

Yuan Zhang[1], Xiang Li[1], Xing Qian[2] and Xiaolin Zhou[1,2,3]*

[1] Center for Brain and Cognitive Sciences and Department of Psychology, Peking University, Beijing, China
[2] Key Laboratory of Child Development and Learning Science (Ministry of Education), Southeast University, Nanjing, China
[3] Key Laboratory of Machine Perception (Ministry of Education), Peking University, Beijing, China
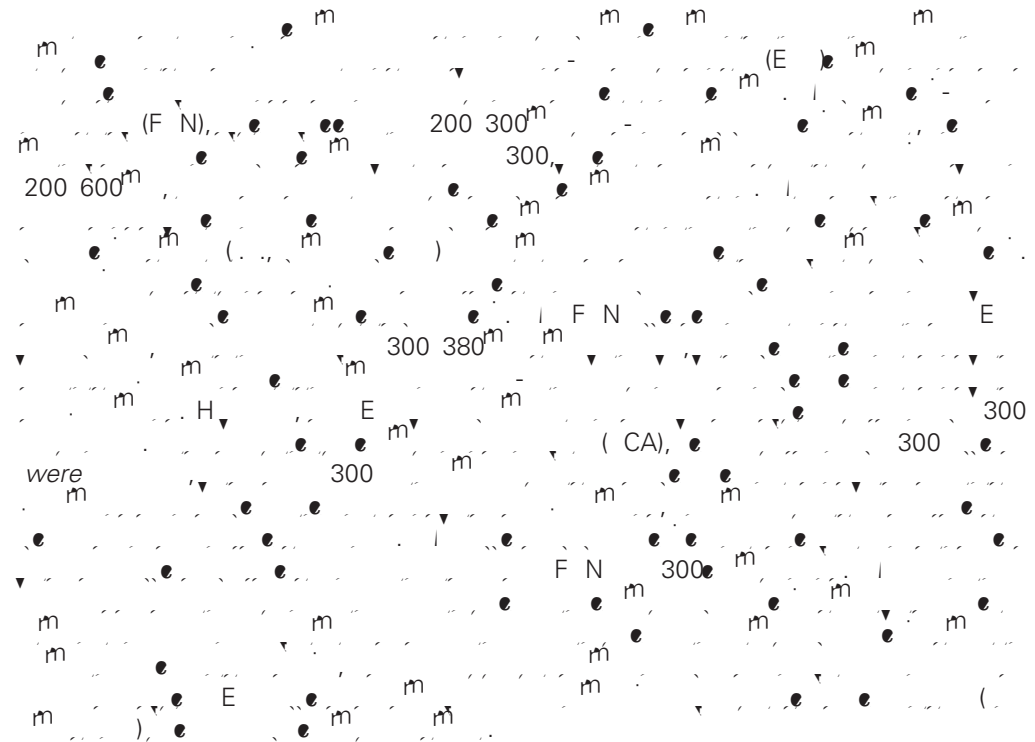
Keywords: outcome evaluation, performance monitoring, facial attractiveness, ERP, FRN, P300, PCA

INTRODUCTION

Over the past decade, there has been increased interest in the neural basis of performance monitoring and outcome evaluation, which plays an important role in decision-making and learning from the environment. Electrophysiological studies on outcome evaluation and performance monitoring have consistently observed two event-related potential (ERP) components (Miltner et al., 1997; Gehring and Willoughby, 2002; Holroyd and Coles, 2002; Nieuwenhuis et al., 2004). The first component, the feedback-related negativity (FRN), is a negative deflection at frontocentral recording sites that typically reaches a maximum amplitude around 250 ms post-onset of the feedback stimulus. It is sensitive to the outcome valence, being more negative-going for negative feedback associated with unfavorable outcomes, such as incorrect responses (Miltner et al., 1997), monetary losses (Gehring and Willoughby, 2002), or violations of expectancy (Heldmann et al., 2008; Wu and Zhou, 2009), than for positive feedback. Another ERP component, the P300, is the most positive peak in the 200–600 ms period post-onset of feedback stimulus and typically increases in magnitude from frontal to parietal sites.

The P300 is traditionally believed to reflect processes demanding attentional resources (Polich and Kok, 1995; Polich, 2007) and it has been found to be related to various aspects of outcome evaluation, including the magnitude of reward (Yeung and Sanfey, 2004; Sato et al., 2005), expectancy toward the outcome (Hajcak et al., 2005, 2007; Wu and Zhou, 2009), and the valence of the outcome (Hajcak et al., 2005, 2007; Wu and Zhou, 2009; Leng and Zhou, 2010).

Almost all the previous studies about outcome evaluation and performance monitoring employed relatively simple tasks (e.g., making a gambling choice or estimating time duration elapsed for a simple visual stimulus), with feedback stimuli that demand little perceptual or cognitive processing (e.g., numerals representing monetary reward or symbols indicating the correctness of estimation). However, in our daily life, we often encounter more complex feedback stimuli, which require sophisticated cognitive processing, particularly stimuli that are important in social interactions (e.g., faces). Moreover, we often make judgments or predictions based on limited information. The later outcome evaluation may involve an implicit comparison that checks the

previous judgment or expectancy stored in memory against the newly available information. For example, when we think we recognize a friend from distance we might want to approach and greet him. Only when we come closer do we see details of his face and realize that he is not the expected person. During the time between seeing the individual from afar and approaching him, we form expectations toward meeting a particular person based on partial information; the later implicit comparison between the new information and the initial expectation allows us to see whether our initial expectation or judgment was correct. It is not clear to what extent the pattern of brain responses to the new, complex feedback information is affected by the result of comparison (i.e., the consistency between the initial judgment or expectation and new information) and by the neurocognitive processes associated with the complex feedback stimulus itself.

The main purpose of this study is to investigate to what extent the neural correlates of the (implicit) outcome evaluation involving complex feedback stimuli (e.g., faces) are similar to those revealed for simple feedback in gambling or simple cognitive tasks. Answers to this question may open a new avenue for the use of the ERP technique to investigate the neural basis of outcome evaluation and performance monitoring in more complex, including social, situations. To mimic a situation in which limited information is available for decision-making and the feedback stimuli require sophisticated processing, we blurred photos of female faces and asked participants to judge whether a presented female face was attractive or unattractive. Photos of unblurred faces were presented as feedback and ERPs time-locked to the onset of the feedback were measured. Facial attractiveness is a key feature in social interactions, such as peer and mate choice (Etcoff, 1999; Thornhill and Gangestad, 1999; Johnston, 2006) and inferences about that individual's personality (Dion et al., 1972). If participants did make (implicit) comparisons between newly available information and previous judgments, then the feedback faces would carry information concerning the valence of feedback (consistent vs. inconsistent with the initial judgment), in addition to information concerning facial attractiveness. The processing of the social aspect of the feedback faces (i.e., attractiveness) becomes a necessary step in deciding whether the initial judgment or guess was right. A previous study found that the ventral occipital region including the fusiform face area (FFA) shows differential responses to attractive and unattractive faces even when the task is beauty-irrelevant (e.g., in an identity judgment task), indicating that facial attractiveness may be processed automatically (Chatterjee et al., 2009).

If the neural correlates of outcome evaluation for complex feedback stimuli with a social dimension are similar to those revealed for simple stimuli, inconsistent faces (those whose attractiveness is inconsistent with the initial judgment) should show an FRN effect relative to consistent faces. On the other hand, previous studies demonstrated that the P300 is sensitive to the reward valence in monetary gambling tasks (Hajcak et al., 2005, 2007; Wu and Zhou, 2009; Leng and Zhou, 2010), with more positive amplitudes for positive feedback than for negative feedback. If so, the P300 should be more positive to feedback faces consistent with the initial judgment than to faces inconsistent with the judgment. Moreover, previous studies also showed that ERP responses are

more positive to attractive faces than to unattractive faces on late positive potential (LPP) or P300 (Johnston and Oliver-Rodriguez, 1997; Oliver-Rodríguez et al., 1999; Werheid et al., 2007; Schacht et al., 2008). We, therefore, predict a P300 or LPP effect for facial attractiveness in this study.

METHOD

PARTICIPANTS

Sixteen right-handed undergraduate students (eight females, 18–24 years, mean = 21) from Peking University participated in the experiment. All the participants had normal or corrected-to-normal vision, and had no history of neurological, psychiatric, or cognitive disorders. This study was conducted in accordance with the Declaration of Helsinki and was approved by the Academic Committee of the Department of Psychology, Peking University.

DESIGN AND MATERIALS

This experiment had a 2 by 2 factorial design, with the first experimental factor (consistency: consistent vs. inconsistent) referring to whether the attractiveness of feedback faces were consistent with the initial judgment and the second experimental factor (attractiveness: attractive vs. unattractive) referring to the facial attractiveness of the feedback faces. The experiment included pre-test, EEG test, and post-test. In the pre-test, 170 attractive and 170 unattractive gray-scale photos of female faces were selected from the photo pools of Peking University and the Institute of Psychology, Chinese Academy of Sciences, based on a consistent rating of above five or below three on a seven-point scale by 20 participants who did not participate in the EEG test. The experimental stimuli in the EEG test comprised of five attractive and five unattractive blurred female faces and the 170 attractive and 170 unattractive unblurred female faces used in the pre-test. Given that there were variable ratings as to whether particular male faces were attractive, we did not include male faces in this study. The attractiveness of unblurred female faces was confirmed in which the EEG participants were asked to rate these faces in the same way as the pre-test. Both the attractive and unattractive faces were unfamiliar to the EEG participants to exclude the influence of familiarity.

We adjusted all photos to be approximately 218 pixels in width (SD = 10.3 pixels) and 274 pixels in height (SD = 4.6 pixels), centered on a 260 pixels × 280 pixels black background. The brightness of all photos was adjusted to about 97.8 (SD = 6.0) as indicated in the histogram after undergoing the "auto laves" function on Adobe Photoshop CS2. Five attractive and five unattractive faces were blurred by Gaussian filters with σ = 14 pixels, maintaining all frequencies below four cycles per photo width.

In each trial in the EEG test, participants were instructed to guess the attractiveness of a blurred face, and to simply watch the subsequent unblurred face, which served as implicit feedback to the consistency of the initial judgment. The blurred faces were presented randomly while the 170 attractive and the 170 unattractive feedback faces were presented in pseudo-random orders. For each participant, each of the blurred faces was presented 34 times and each of the attractive or unattractive faces was presented only once, with the restriction that no more than three consecutive

feedback faces were from the same category. Different pseudo-random orders were created for different participants. Unknown to the participants, the blurred face in each trial was not the same one as the feedback face. The purpose of this manipulation was to exclude the potential influence of the blurred faces on the perceptual processing of the subsequent feedback faces as well as to make sure that about half of the trials would constitute "consistent" trials.

PROCEDURES

Participants were seated in a sound-attenuated, electrically shielded chamber approximately 1 m from a computer screen. At the start of each trial, at the center of the computer screen, a white fixation cross ($0.6° \times 0.6°$ in visual angle) was presented against a black background for 500 ms. Then a blurred black-and-white face photo was presented ($6.3° \times 4.6°$), and remained on the screen until the participant's response (**Figure 1**). The participants' task was to make a binary attractiveness judgment as quickly as possible, by pressing a key on a joystick using their left or right index finger. Button assignment was counter-balanced between participants. After the response, a fixation cross was presented again for 800 ms. Then a unblurred face photo ($6.3° \times 4.6°$), serving as feedback to the participants' initial judgment, was presented for 800 ms, and participants were asked to simply watch it and wait for the next trial. After the unblurred face, a fixation cross was presented for 700 ms and the screen turned black for 100 ms before the next trial began.

Before the EEG test, participants completed a practice block consisting of 10 trials to make sure they understood the task. The EEG test consisted of four blocks with 85 trials each. After the EEG test, participants completed a post-test, rating the attractiveness of each feedback face that had appeared in the EEG test. For faces which a participant's rating in the post-test was inconsistent with the predefined attractiveness, the corresponding trial with that face in the formal test was excluded from EEG data analysis.

EEG RECORDING

The EEG was recorded continuously from 62 scalp electrodes mounted on an elastic cap (NeuroScan Inc., Herndon, Virginia, USA) according to the extended 10–20 system with the addition of two mastoid electrodes. Signals were referenced online to the left mastoid and were re-referenced offline to the linked mastoids. Eye blinks and vertical eye movements were monitored with electrodes located above and below the left eye. The horizontal electro-oculogram was recorded from electrodes placed 1.5 cm lateral to the left and right external canthi. The electrode impedance was less than 5 kΩ. The EEG was amplified (bandpass 0.05–100 Hz) and digitized at 500 Hz.

DATA ANALYSIS

ERPs were computed for each participant over an epoch from 200 ms before to 800 ms after the onset of the feedback faces, with the 200 ms pre-stimulus EEG activity used for baseline correction. Ocular artifacts were corrected with an eye-movement correction
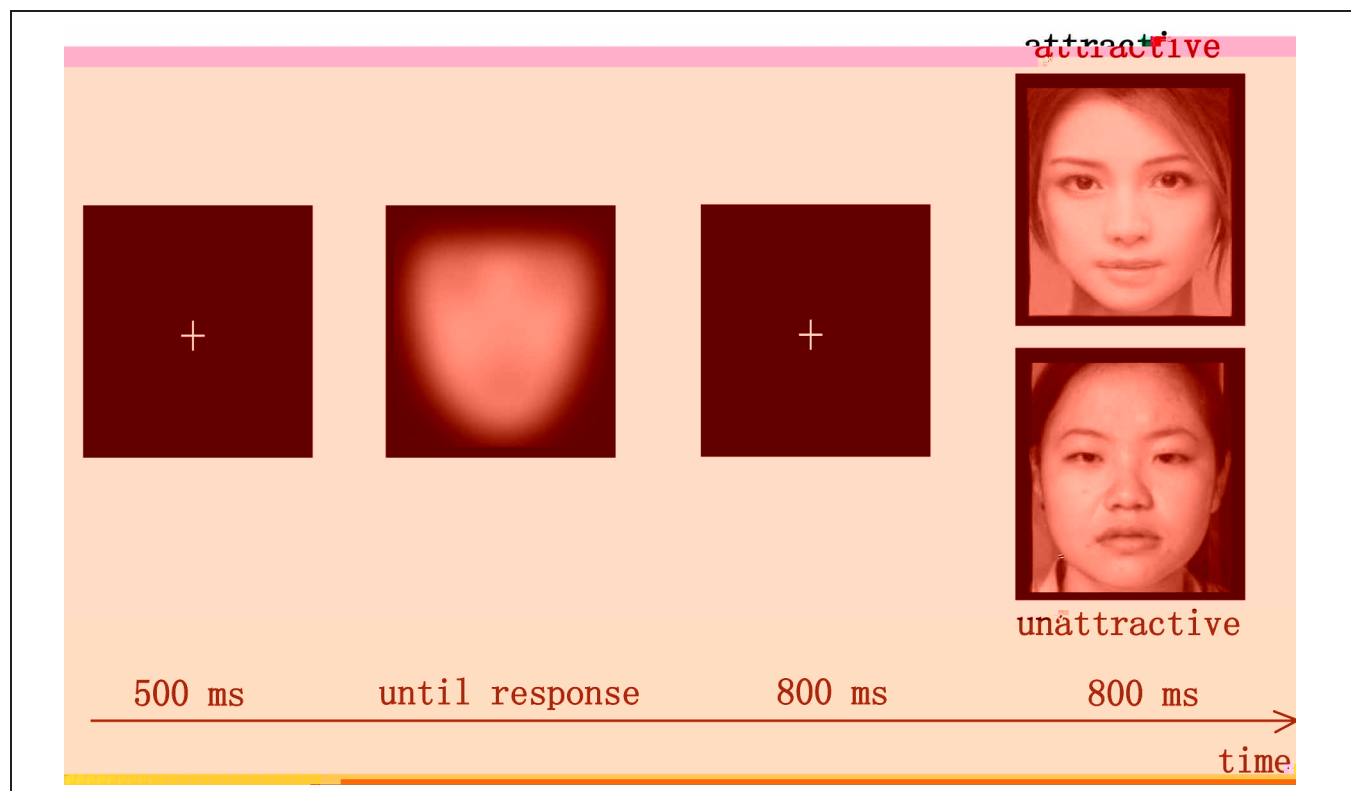

FIGURE 1 | Sequence of events in a single trial.

algorithm which employs a regression analysis in combination with artifact averaging (Semlitsch et al., 1986). Epochs contaminated by blinks and other movement artifacts were excluded from averaging using an 80 μV criterion. The EEG data were low-pass filtered at 30 Hz and were baseline-corrected by subtracting the average activity of that electrode during the baseline period from each trial. After excluding trials with artifacts, each participant had at least 46 trials in each condition.

The grand-average ERP waveforms (**Figure 2**) did not show a typical pattern for ERP responses that were observed for feedback stimuli in gambling or simple cognitive tasks (e.g., no clear P300 component was visible), although it appeared that inconsistent faces elicited negative-going deflections in the 300–380 ms time window. We, therefore, analyzed ERP responses in different conditions in the windows of 150–220 ms (i.e., P200), 300–380 ms (i.e., FRN), and 380–500 ms based on visual inspection. For the purposes of statistical analysis, mean amplitudes for each time window was calculated across 25 electrode locations (F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, P4) that were chosen to cover scalp areas known from previous studies to be the focus of the FRN and P300. A repeated-measures analysis of variance (ANOVA) was conducted, with attractiveness (attractive vs. unattractive), feedback consistency (consistent vs. inconsistent), anterior-posterior scalp location (frontal, frontocentral, central, centroparietal, parietal), and lateral scalp location (left, left central, midline, right central, right) as four within-subjects experimental factors. The Greenhouse-Geisser correction for violation of the ANOVA assumption of sphericity was applied in all analysis. Bonferroni corrections were used for multiple comparisons.

Given that the processing of the feedback faces and their attractiveness was likely to involve sophisticated neurocognitive pro-

(PCA) on the *cleaned* ERP data (i.e., after preprocessing) in order to disentangle the overlapping and/or masked ERP components. PCA has a wide range of applications in ERP analysis, such as cleaning or filtering noises prior to data analysis, or being used in data exploration as a way to detect and summarize features of the dataset. In this study, we applied PCA on the cleaned ERP data to maximize the possibility that the PCA factors represent interpretable signals (i.e., brain activity due to experimental manipulations) as opposed to noise (i.e., artifacts or background EEG).

PCA is a common approach for decomposing an ERP dataset into its constituent factors by summarizing the relationship between variables (such as microvolt recordings at each time point in temporal PCA or at each electrode in spatial PCA; Dien and Frishkoff, 2005; Dien et al., 2005). This process consists of three main steps: (1) computation of the covariance matrix which captures the interrelationships between temporal/spatial variables; (2) extraction and retention of the PCA factors which extract linear combinations of variables (latent factors) to account for patterns of covariance in the ERP data with the fewest PCA factors; and (3) rotation to simple structure, which is used to restructure the allocation of variables to PCA factors to maximize the chance that each PCA factor reflects a single ERP component. These steps yield two matrices, which are useful in further analysis. The first one is a factor loading matrix, representing correlations between the variables and the factor scores (e.g., describing the time course of each of the PCA factors in temporal PCA). The second one is a factor score matrix that indexes the magnitude of the PCA factors for each of the observations, reflecting the contribution of each PCA factor to ERPs.

In this study, we used the spatiotemporal PCA algorithm implemented in the Matlab ERP PCA toolbox 2.23 (Dien and Frishkoff, 2005; http://sourceforge.net/projects/erppcatoolkit/files). In the spatiotemporal PCA, a spatial PCA was performed first on the ERP data from all the electrodes to capture spatial distribution, with the combination of 501 time points (covering the epoch from −200 to 800 ms post-onset of the feedback stimuli), 16 participants and four experimental conditions. Infomax rotation was used, and two spatial factors were extracted based on the resulting Scree plot. For each spatial factor, this analysis yielded factor scores for each combination, representing the amount of activity in the original data captured by that factor. A temporal PCA was then performed for each of the two spatial factors. Promax rotation was used, and four temporal factors were extracted based on the Scree plot, yielding eight unique factors combinations (i.e., two spatial factors by four temporal factors). The covariance relationship matrix and Kaiser normalization were used for each PCA. The waveforms for each factor combination were reconstructed (i.e., converted to microvolts) by multiplying the factor pattern matrix with the standard deviations. A PCA factor may contain one or more known ERP components, or may contain no well-defined or theoretically interesting ERP components. Following the suggestion of Dien et al. (2005) and based on visual inspection of the waveforms associated with each PCA factor, two factors that contained known ERP components involved in outcome evaluation and facial attractiveness (i.e., P300) were selected

for further statistical analysis, with attractiveness (attractive vs. unattractive) and feedback consistency (consistent vs. inconsistent) as two within-subjects experimental factors. Here we focused on electrodes that showed the largest effect for each selected PCA factor. The Greenhouse–Geisser correction was applied for violation of the ANOVA assumption of sphericity.

RESULTS

BEHAVIORAL RESULTS

In the post-test on the attractiveness of the feedback faces, 377 trials (6.9%) in total were inconsistent with the categorization of attractiveness based on the pretest (i.e., their rating scores were below five for attractive faces or above three for unattractive faces). After excluding the EEG trials corresponding to these faces, the remaining 5063 trials were categorized into four conditions: attractive-consistent (72 trials per participant on average, ranging from 51 to 117 trials over participants), attractive-inconsistent (78 trials on average, ranging from 48 to 100 trials), unattractive-consistent (91 trials on average, ranging from 61 to 117 trials), and unattractive-inconsistent (76 trials on average, ranging from 48 to 107 trials). Overall, the percentage of trials (out of all the available trials) for each condition was 22.6%, 24.5%, 28.9%, and 24.0%, respectively. No statistically significant differences were found between the conditions.

ERP RESULTS

ERP waveforms time-locked to the onset of feedback faces and topographic distributions of the differences between conditions (e.g., ERP effects) in three time windows are illustrated in **Figures 2** and **3**, respectively.

For the 150–220 ms time window (**Figures 2**, **3**), repeated-measures ANOVA showed a significant main effect of attractiveness, $F(1,15) = 18.39$, $p = 0.01$, with more positive P200 responses to attractive faces ($5.95\,\mu$V) than to unattractive ones ($4.98\,\mu$V). The interaction between attractiveness and lateral scalp location was significant, $F(4,60) = 5.17$, $p = 0.001$, indicating that the size of the P200 effect varied over different scalp locations. No other significant effects were found.

For the 300–380 ms window, ANOVA showed a significant main effect of feedback consistency, $F(1,15) = 15.99$, $p = 0.001$, with ERP responses to feedback faces more negative-going following inconsistent judgments ($9.97\,\mu$V) than following consistent judgments ($11.36\,\mu$V). The main effect of attractiveness was also significant, $F(1,15) = 20.48$, $p < 0.001$, with more negative-going responses to unattractive faces ($9.56\,\mu$V) than to attractive ones ($11.78\,\mu$V). The interaction between attractiveness and feedback consistency was not significant, $F(1,15) < 1$, indicating that the attractiveness effect was not affected by feedback consistency. The interaction between attractiveness and anterior-posterior scalp location was significant, $F(4,60) = 17.66$, $p < 0.001$, as was the interaction between attractiveness and lateral scalp location, $F(4,60) = 8.21$, $p = 0.01$. It is clear from **Figure 3** that the attractiveness effect in this time window was strongest in the frontocentral regions. No other significant effects were found.

To further verify the feedback consistency effect, we carried out statistical analyses based on peak-to-peak measurements of the feedback consistency responses (Sato et al., 2005; Wu and Zhou,
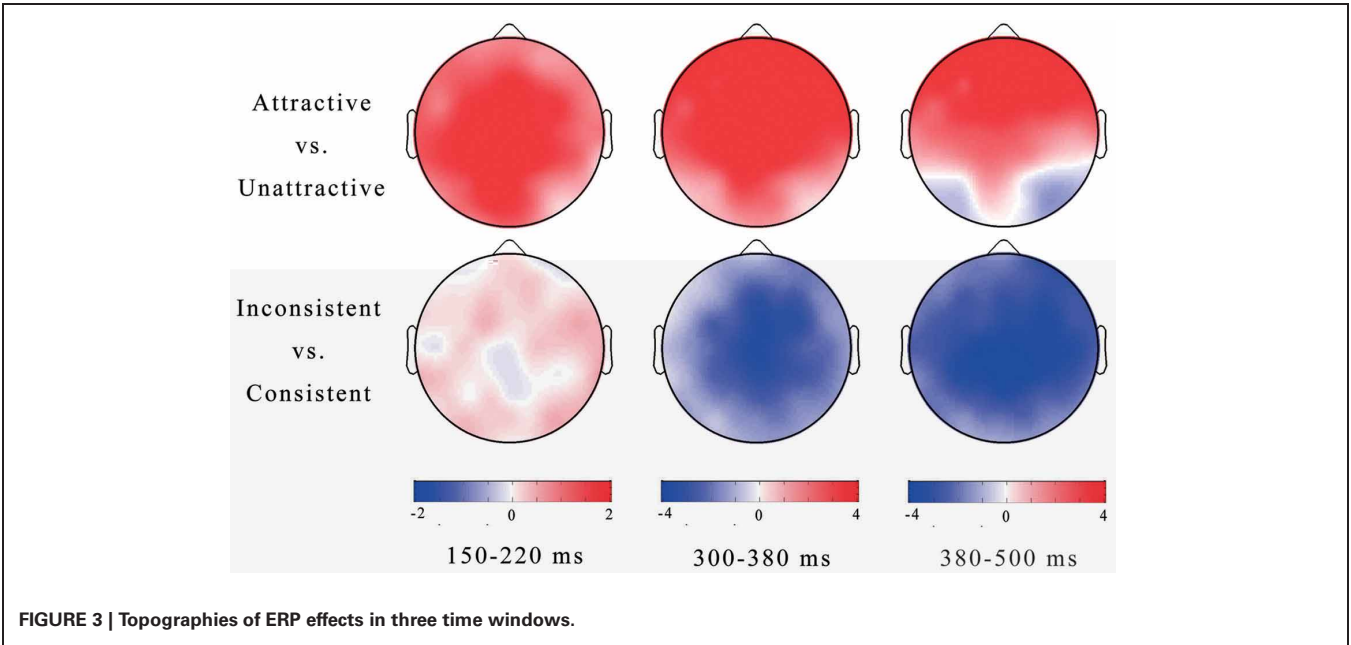
FIGURE 3 | Topographies of ERP effects in three time windows.

2009), with the most negative amplitudes in the 300–380 ms window and the most positive amplitudes in the 220–300 ms window as peaks. Consistent with the above analysis, the main effect of feedback consistency was significant, $F(1,15) = 15.38, p = 0.001$, and this effect did not interact with attractiveness, $F(1,15) < 1$. The main effect of attractiveness was significant, $F(1,15) = 20.51$, $p < 0.001$.

For the 380–500 ms window, ANOVA showed a significant main effect of attractiveness, $F(1,15) = 13.31$, $p < 0.01$, with
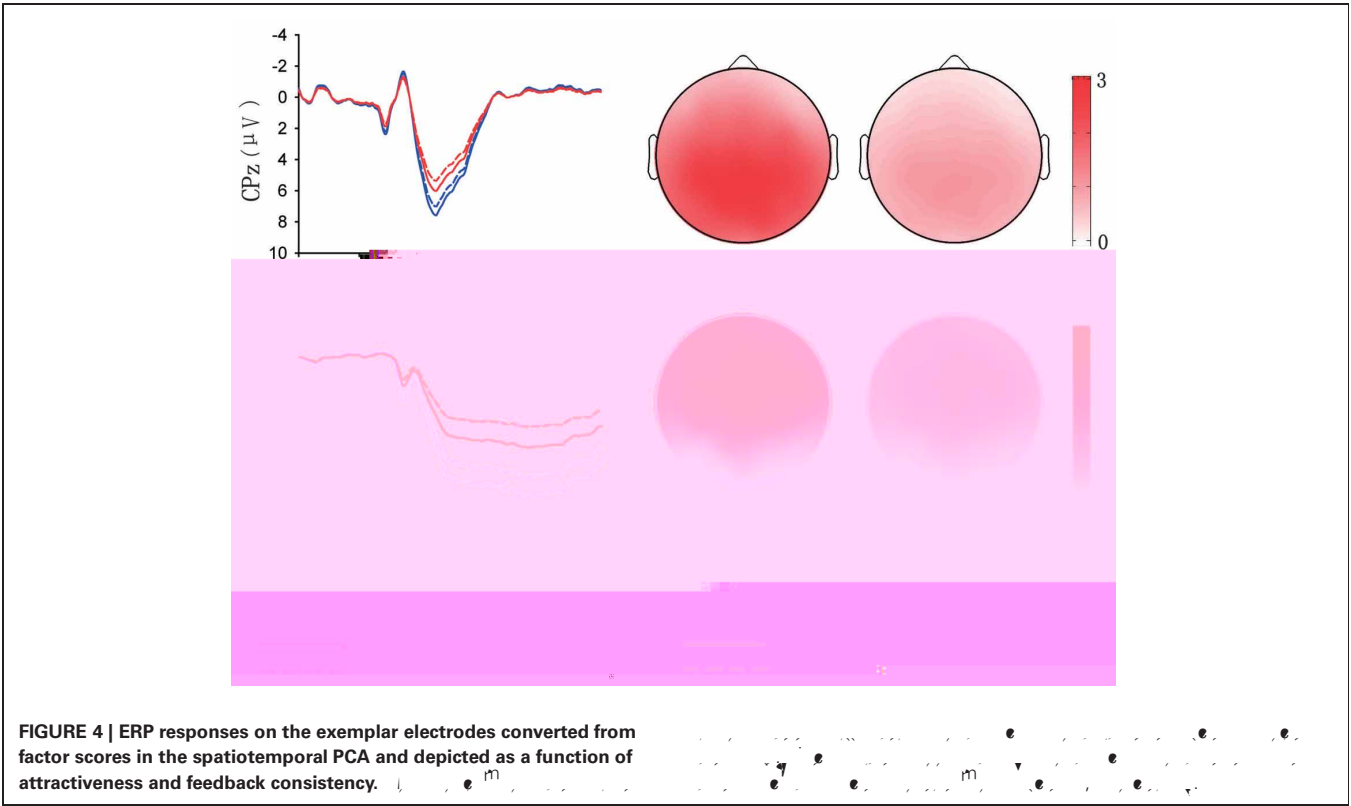
FIGURE 4 | ERP responses on the exemplar electrodes converted from factor scores in the spatiotemporal PCA and depicted as a function of attractiveness and feedback consistency.

information would indicate whether the feedback stimuli had properties consistent or inconsistent with the initial judgment.

An FRN effect was observed for inconsistent feedback faces in ERP waveforms, in accordance with many earlier studies (Gehring and Willoughby, 2002; Holroyd and Coles, 2002; Yeung et al., 2005; Leng and Zhou, 2010; Zhou et al., 2010; Long et al., 2012), albeit in a delayed 300–380 ms time window. Faces inconsistent with the initial judgment elicited more negative-going responses than faces consistent with the judgment. The delay of the FRN effect was likely due to the complexity of neurocognitive processes involved in facial attractiveness and feedback consistency processing. To know whether the initial judgment or guess was a correct one, the system has to first process the perceptual structure of the feedback face, and evaluate the attractiveness of this face by appealing to experiences or schemas stored in long-term memory, and secondly to compare the result of this evaluation with information concerning the initial judgment stored in working memory. It takes time to accomplish these processes, delaying the appearance of the FRN effect, even though assessing facial attractiveness can be fairly automatic (Chatterjee et al., 2009). A previous study has also shown that the FRN effect was delayed when the sophisticated counter-factual thinking was involved in accessing the outcome valence of gambling choices (Yu and Zhou, 2009).

However, the ERP waveforms did not show the typical pattern of P300 responses; instead, sustained deflections were observed, with significant main effects for attractiveness and feedback consistency. We suspected that the usual P300 responses were masked by the sophisticated cognitive (and emotional) processes involved

in processing the feedback faces, and the observed deflections (and possibly the preceding ERP responses) contained P300 components. We, therefore, conducted spatiotemporal PCA, which revealed a clear pattern of P300 effects for both feedback consistency and attractiveness, with more positive responses to those faces consistent with the initial judgment than to faces inconsistent with the judgment, and more positive responses to attractive faces than to unattractive ones. Moreover, the P300 effects centered on centroparietal areas lasted for a short time period while the P300 effects centered on frontocentral area sustained for a long time period, indicating that facial attractiveness and feedback consistency could be processed parallel in different brain areas.

The P300 effect for feedback consistency or valence replicated previous studies using gambling tasks (Hajcak et al., 2005, 2007;

(Polich and Kok, 1995; Polich, 2007). The independence between the P300 effect for feedback consistency and the effect for facial attractiveness, while replicating previous studies that simultaneously manipulated different dimensions of feedback stimuli (Hajcak et al., 2005, 2007; Wu and Zhou, 2009; Long et al., 2012), indicate that the evaluative processes for different dimensions of the outcome can be conducted in parallel.

Note that we also found a significant main effect of attractiveness in the 300–380 ms window. However, we do not interpret it as a kind of FRN effect because we believe this effect was very likely due to the spillover of the P300 effects for facial attractiveness.

To conclude, this study provides the first demonstration of electrophysiological responses in outcome evaluation with complex feedback stimuli (e.g., faces) that need complicated neurocognitive processing. We demonstrated that the ERP correlates of processing complex feedback stimuli with a social dimension are generally similar to those involved in processing simplex feedback stimuli; however, appropriate means of ERP data analysis, including PCA, may be needed to uncover the underlying patterns of effects that might be masked by the sophisticated processes associated with the complex stimuli themselves. Consistent with previous studies, the present study demonstrates again that the FRN reflects early assessment of outcome valence while the P300 can encode different attributes of feedback simultaneously in outcome evaluation and performance monitoring.

REFERENCES

Aharon, I., Etcoff, N., Ariely, D., Chabris, C. F., O'Connor, E., and Breiter, H. C. (2001). Beautiful faces have variable reward value: fMRI and behavioral evidence. *Neuron* 32, 537–551.

Bray, S., and O'Doherty, J. (2007). Neural coding of reward-prediction error signals during classical conditioning with attractive faces. *J. Physiol.* 98, 3036–3045.

Chatterjee, A., Thomas, A., Smith, S. E., and Aguirre, G. K. (2009). The neural response to facial attractiveness. *Neuropsychology* 23, 135–143.

Cloutier, J., Heatherton, T. F., Whalen, P. J., and Kelley, W. M. (2008). Are attractive people rewarding? Sex differences in the neural substrates of facial attractiveness. *J. Cogn. Neurosci.* 20, 941–951.

Dien, J., Beal, D. J., and Berg, P. (2005). Optimizing principal components analysis of event-related potentials: matrix type, factor loading weighting, extraction, and rotations. *Clin. Neurophysiol.* 116, 1808–1825.

Dien, J., and Frishkoff, G. A. (2005). "Introduction to principal components analysis of event-related potentials," in *Event-related Potentials: A Methods Handbook*, ed T. Handy (Cambridge, MA: MIT Press), 189–208.

Dion, K., Berscheid, E., and Walster, E. (1972). What is beautiful is good. *J. Pers. Soc. Psychol.* 24, 285–290.

Etcoff, N. (1999). *Survival of the Prettiest: The Science of Beauty*. New York, NY: Doubleday.

Gehring, W. J., and Willoughby, A. R. (2002). The medial frontal cortex and the rapid processing of monetary gains and losses. *Science* 295, 2279–2282.

Hajcak, G., Holroyd, C. B., Moser, J. S., and Simons, R. F. (2005). Brain potentials associated with expected and unexpected good and bad outcomes. *Psychophysiology* 42, 161–170.

Hajcak, G., Moser, J. S., Holroyd, C. B., and Simons, R. F. (2007). It's worse than you thought: the feedback negativity and violations of reward prediction in gambling tasks. *Psychophysiology* 44, 905–912.

Heldmann, M., Russeler, J., and Munte, T. (2008). Internal and external information in error processing. *BMC Neurosci.* 9, 33–40.

Holroyd, C. B., and Coles, M. G. H. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychol. Rev.* 109, 679–709.

Ishai, A. (2007). Sex, beauty and the orbitofrontal cortex. *Int. J. Psychophysiol.* 63, 181–185.

Johnston, V. S. (2006). Mate choice decisions: the role of facial beauty. *Trends Cogn. Sci.* 10, 9–13.

Johnston, V. S., and Oliver-Rodriguez, J. C. (1997). Facial beauty and the late positive component of event-related potentials. *J. Sex Res.* 34, 188–198.

Kampe, K. K. W., Frith, C. C., Dolan, R. J., and Frith, U. (2001). Reward value of attractiveness and gaze. *Nature* 413, 589–590.

Leng, Y., and Zhou, X. (2010). Modulation of the brain activity in outcome evaluation by interpersonal relationship: an ERP study. *Neuropsychologia* 48, 448–455.

Long, Y., Jiang, X., and Zhou, X. (2012). To believe or not to believe: trust choice modulates brain responses in outcome evaluation. *Neuroscience* 200, 50–58.

Miltner, W. H. R., Braun, C. H., and Coles, M. G. H. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: evidence for a "generic" neural system for error detection. *J. Cogn. Neurosci.* 9, 787–796.

Nieuwenhuis, S., Holroyd, C. B., Mol, N., and Coles, M. G. H. (2004). Reinforcement-related brain potentials from medial frontal cortex: origins and functional significance. *Neurosci. Biobehav. Rev.* 28, 441–448.

O'Doherty, J., Winston, J., Critchley, H., Perrett, D., Burt, D. M., and Dolan, R. J. (2003). Beauty in a smile: the role of medial orbitofrontal cortex in facial attractiveness. *Neuropsychologia* 41, 147–155.

Oliver-Rodríguez, J. C., Guan, Z., and Johnston, V. S. (1999). Gender differences in late positive components evoked by human faces. *Psychophysiology* 36, 176–185.

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin. Neurophysiol.* 118, 2128–2148.

Polich, J., and Kok, A. (1995). Cognitive and biological determinants of P300: an integrative review. *Biol. Psychol.* 41, 103–146.

Sabatinelli, D., Flaisch, T. C., Bradley, M. M., Fitzsimmons, J. R., and Lang, P. J. (2004). Affective picture perception: gender differences in visual cortex? *Neuroreport* 15, 1109–1112.

Sato, A., Yausda, A., Ohira, H., Miyawaki, K., Nishikawa, M., Kumano, H., and Kuboki, T. (2005). Effects of value and reward magnitude on feedback negativity and P300. *Neuroreport* 16, 407–411.

Schacht, A., Werheid, K., and Sommer, W. (2008). The appraisal of facial beauty is rapid but not mandatory. *Cogn. Affect. Behav. Neurosci.* 8, 132–142.

Semlitsch, H. V., Anderer, P., Schuster, P., and Presslich, O. (1986). A solution for reliable and valid reduction of ocular artifacts, applied to the P300 ERP. *Psychophysiology* 23, 695–703.

Thornhill, R., and Gangestad, S. W. (1999). Facial attractiveness. *Trends Cogn. Sci.* 3, 452–460.

Werheid, K., Schacht, A., and Sommer, W. (2007). Facial attractiveness modulates early and late event-related brain potentials. *Biol. Psychol.* 76, 100–108.

Winston, J. S., O'Doherty, J., Kilner, J. M., Perrett, D. I., and Dolan, R. J. (2007). Brain systems for assessing facial attractiveness. *Neuropsychologia* 45, 195–206.

Wu, Y., and Zhou, X. (2009). The P300 and reward valence, magnitude, and expectancy in outcome evaluation. *Brain Res.* 1286, 114–122.

Yeung, N., Holroyd, C. B., and Cohen, J. D. (2005). ERP correlates of

feedback and reward processing in the presence and absence of response choice. *Cereb. Cortex* 15, 535–544.

Yeung, N., and Sanfey, A. G. (2004). Independent coding of reward magnitude and valence in the human brain. *J. Neurosci.* 24, 6258–6264.

Yu, R., and Zhou, X. (2009). To bet or not to bet? The error negativity or error-related negativity associated with risk-taking choices. *J. Cogn. Neurosci.* 21, 684–696.

Zhou, Z., Yu, R., and Zhou, X. (2010). To do or not to do? Action enlarges the FRN and P300 effects in outcome evaluation. *Neuropsychologia* 48, 3606–3613.

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.