Multi-Target Positive Emotion Recognition From EEG Signals

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Abstract—Compared with the widely studied negative emotions in which different classes are easy to distinguish, nowadays less attention is paid to the recognition of positive emotions that are not fully independent. In this article, we propose to recognize multiple continuous positive emotions that exhibit statistical dependencies using multi-target regression — by analyzing brain activities when an individual watches emotional film clips — and explore the neural representation of different positive emotions. Thirty-seven participants volunteered to participate in our study, in which their brain activities were recorded when watching five selected film clips (corresponding to five positive emotions: amusement, happiness, romance, tenderness and warmth). First, 150 well-known power features extracted from Electroencephalography (EEG) signals and 105 multimedia content analysis features were collected as the pool of candidate features. Second, based on the collected features, we propose to use a linear model (linear regression) and a nonlinear model (long short-term memory network, LSTM) to predict the percentage of five positive emotions. Then, percentage values were converted to ranking numbers and Kendall rank correlation coefficients were calculated. Our results showed that (1) ensemble of regressor chains (ERC) using LSTM as unit regressor obtained both the best regression results (with lowest RMSE $= 8.325$ and highest $\mathrm{R}^2 = 0.346$) and the best Kendall rank correlation coefficient (0.165) on EEG features merely, and (2) selective features from alpha frequency bands of EEG signals could represent different positive emotions. These results demonstrate the effectiveness of selective EEG features on recognizing different positive emotions.

Index Terms—Emotion recognition, positive emotion, multi-target, regression model, EEG

1 Introduction

Emotions are one of the core components of human psychology and behavior associated with cognition, physiological reactions, and actions. Emotion recognition is a key technique in affective computing and plays an important role in the advanced human-machine interaction. Over past decades, negative emotions have long been the focus of typical emotion research such as depression, anxiety, fear, etc. However, less attention has been paid to the form and function of different positive emotions. Recently, the emerging field of positive psychology, which emphasize the importance of positive affective states, personality trait and social system, has called for a shift of researchers' attention towards detailed characteristics of positive emotions [1], [2].

The recognition of positive emotions is of great significance in people's daily life due to the wide application and the constructive function of positive emotions [3]. For example, positive product experience such as 'exciting', 'unforgettable', 'excellent' and 'pleasant' have been used to define the quality of emotional human-computer interaction [4]. The undoing effect of positive emotion refers to the undoing of physiological arousal produced by negative emotions, which has been proven to be benefit for social interaction such as marital interaction [5]. What's more, positive emotions can facilitate integrative and associative information processing in cognitive functions [6], [7], promote adaptive social functioning [8], [9], and help to prevent and treat psychological symptoms [10]. Different positive emotions have been proposed to have different functional roles [11], [12]. For instance, amusement is a self-based emotion associated with something funny, whereas romance is a feeling on the basis of the interpersonal relationship. Effective recognition and analysis of positive emotions can make better use of the constructive role of positive emotions.

The majority of studies on emotion recognition were built on typical emotion models such as discrete model or dimensional model to classify emotions into discrete emotional categories or valence-arousal dimensions. Although "positive" as one side of valence dimension opposed to "negative" has long been accepted to represent emotion in traditional taxonomies of discrete model [13], there is only one positive emotion for every four or five negative emotions which has been widely studied from the perspective of discrete model (e.g., 'happy' versus 'anger','fear','sad' and 'disgust' [14]). One possible reason is that positive emotions are highly correlated and most positive feelings are under the umbrella of happiness. However, evidences had

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Manuscript received 27 February 2020; revised 14 October 2020; accepted 3 December 2020. Date of publication 8 December 2020; date of current version 28 February 2023.
(Corresponding author: Yong-Jin Liu.)
Recommended for acceptance by W. Zheng.
Digital Object Identifier no. 10.1109/TAFFC.2020.3043135

been provided to show that individuals can experience and report more different positive emotions than happiness [15]. Thus, more positive emotion categories should be taken into consideration in the field of emotion recognition.

Since different positive emotions are not easy to distinguish clearly from each other compared to negative emotions in subjective experience, a model specially designed for recognizing positive emotions is desired. This recognition problem is very challenging, partially because the exploration of the possible corresponding differentiation in their neural correlates is also very limited. Therefore, the present study aimed to establish an electroencephalography (EEG)-based multi-target recognition model for positive emotions, which will provide support for exploring the mechanism of positive emotions, accurately identifying positive emotions through multi-modal signals and rationally applying positive emotions.

1.1 Literature Review

1.1.1 Discrete Positive Emotion

While the arousal-valence model has been popular in the affective computing field, its capacity in differentiating positive emotions has been criticized. The above-mentioned two positive emotions, amusement and romance, for instance, might not be easily separated in their arousal and valence dimensions. Alternatively, it has been reported that emotions can be more easily captured by words of discrete subjective feeling such as "feel amused" rather than by dimensions such as arousal and valence in daily life when people describe their emotional states [15].

And lots of efforts have been devoted to the categorization of different positive emotions, mostly based on subjective reports. For instance, ten positive emotions are included in the well-known PANAS scale (Positive Affect and Negative Affect Scale) [16]; likewise, another set of ten positive emotions were suggested for their representativeness of daily life emotions [17]; in a recent study which includes 27 distinct categories of emotions, more than half of them can be considered as positive [15].

1.1.2 Positive Emotion Recognition Using EEG Signal

In contrast to the prosperity in emotion construction theories, the behavioral and neurophysiological studies have for a long time focused on only typical individual positive emotion, such as happiness, joy, and amusement [18], [19], [20], [21]. Systematical investigations into the possible differences among distinct positive emotions have gradually gained attention in the past decade.

Bio-signals from our autonomic nervous system (ANS), such as heart rate, heart rate variability, skin conductance, respiration rate, etc., could effectively represent different positive emotions as well. Addressing the functional need for individuals under an evolutionary framework, a five-category positive emotion set was proposed (anticipatory enthusiasm, attachment love, nurturant love, amusement, and awe) and their possible neurophysiological differences were assessed [22]. Using static images to elicit these emotions, the multi-dimensional ANS signals indeed revealed significant distinct patterns.

More importantly and most related to our present study, the neural responses of our central nervous system (CNS) have attracted possibly the greatest attention. Among all possible neuroimaging techniques (e.g., functional magnetic resonance imaging, magnetoencephalography), EEG is the most popular choice for researchers working on affective computing, for its high temporal resolution, high portability and relatively low running cost. With the rapid development of EEG-based emotion recognition techniques, the EEG correlates of basic positive emotional states were explored in addition to the behavioral and subjective experience representations. For example, it was found that alpha band power asymmetry from F3 and F4 electrode sites could be used to distinguish tenderness and amusement [23]. And Heraz, Razaki and Frasson [24] successfully distinguished curious and triumph elicited by pictures from the international affective picture system (IAPS) using k-nearest neighbors (kNN) as a classifier and the amplitudes of four EEG components as features.

Except for emotional pictures, researchers are beginning to use the film-induced EEG signals to classify different positive emotions, however, most of them have merely focused on positive emotions with different arousal levels [25]. For example, Wang, Nie and Lu [26] have classified film-induced relax (low arousal) and joy (high arousal) states with an accuracy of 66.51 percent using the power spectral density (PSD) features extracted from EEG signals.

Considering recognition of discrete positive emotions using EEG signal, a recent EEG study has adopted the ten positive emotion framework proposed by Fredrickson [17]. In their study, film clips were employed to elicit different positive emotions and these emotions were further categorized into three clusters, based on the subjective ratings from the participants [27]. To be specific, awe, gratitude, hope, inspiration, and pride were clustered as 'encouragement', amusement, joy, and interest were clustered as 'playfulness', and love, serenity were clustered as 'harmony'. Further, the binary classification on these positive emotions and three clusters achieved accuracies of approximately 80 percent using spectral power features extracted from EEG signals.

1.1.3 Multi-Target Recognition of Positive Emotions

It has to be pointed out that the subjective feelings of different positive emotions are highly correlated, and it is more difficult to distinguish from each other clearly compared to negative emotions [28], [29]. Especially for film-induced emotion, it is hard to elicit a completely pure emotional state due to the complexity of stimulus. When people are watching positive emotional film clips, they may feel more than one different positive emotions at the same time. Therefore, compared to negative emotion recognition or typical positive emotion recognition, single-target classification and regression cannot model this multiplicity.

Previous studies regarding music-induced emotion recognition cast the emotion classification problem as a multi-label classification since the music can be classified into multiple emotional classes or music types simultaneously. For example, timbral, pitch, rhythm, and loudness features were extracted from music and ratings in the several bipolar adjective pairs were used as multi-emotional targets (e.g., cheerful vs. depressing, relaxing vs. exciting and comforting vs. disturbing). Multi-label classification methods including binary relevance, label power set, random *k*-label-sets, multi-label *k*-nearest neighbor and binary relevance based least squares twin support vector machine were used to predict these adjective pairs [30], [31], [32], [33]. All these studies of music-induced emotion labels were merely based on multimedia content analysis (MCA) features.

In this paper, we follow [56] to distinguish multi-label classification and multi-target regression: both models predict multiple output variables from a series of input variables. If the predicted outputs are binary like the above music-induced emotion study, the task is multi-label classification. Otherwise, the predicted outputs are continuous values and the task is multi-target regression. Since positive emotions are highly correlated, multi-target regression can show the percentage of each positive emotion and is more suitable for positive emotion study.

To model multi-target regression, Kocev, Vens, Struyf and Džeroski [34] applied bagging and random forests to multi-objective decision trees (MODT) [35]. The random forest ensemble of MODT, i.e., multi-objective random forest (MORF) performed better than the bagging for MODT method. Inspired from the random k label-sets (RAkEL) for multi-label classification [36], Tsoumakas, Spyromitros-Xioufis, Vrekou and Vlahavas [37] proposed an ensemble method based on random linear combinations (RLC) of the output space for multi-target regression. The experiments on 12 datasets demonstrated its stronger ability for multi-target regression than single-target (ST) and MORF. Researchers also developed methods to learn sparse representations shared among tasks using regularization based on trace norm, l_1/l_∞ norm, LASSO, etc. [38], [39], [40] for multi-target learning. Recently, Spyromitros-Xioufis, Tsoumakas, Groves and Vlahavas [41] proposed multi-target stacking (MTS) and ensemble of regressor chains (ERC) for multi-target regression. Compared with the baseline ST, MORF, trace norm regularization for multi-task learning, the Dirty approach for multi-task learning, and RLC, MTS and ERC consistently obtained improvements on different datasets.

Because movie clips have several benefits for emotion elicitation compared to other materials [42], the exploration of recognizing movie-induced positive emotions using multi-target regression methods based on EEG features was considered in the current study.

1. 2 Contribution of This Paper

First and most importantly, the present study proposes to address the positive emotion recognition issue from a multi-target perspective. As reviewed above, the limited number of affective computing studies on positive emotions have mainly adopted a categorical perspective [25], [26], [29], i.e., assigning each emotion state with one single positive emotion target. Considering the high correlations among different positive emotion categories [28], [29], we assigned multiple targets to each emotion state, thus allowing a more precise description of people's positive emotion experience.

Second, we employed a multi-target regression method to solve the multi-target recognition problem. The construction of the multi-target emotions as represented by multi-dimensional continuous values, calls for a new recognition framework rather than single-target classification or regression methods. To this end, the present study aims to (1) establish an EEG-based emotion recognition model that can recognize five positive emotions simultaneously when an individual watches emotional film clips, and (2) explore the neural representation of positive emotions from a data-driven perspective. In this paper, EEG signals were recorded when participants were watching five representative film clips. As aforementioned, the general positive emotion recognition task is very challenging. So in this paper we test and compare two specific scenarios, and the analysis of their performance may shed light on the solution to the general problem:

1) *Four-fold cross validation within each film clip:* given an emotional film, we partition the film into a short opening segment and the remaining part. We use a participant's EEG signals of watching the opening segment for training and predict multiple positive emotions using the same participant's EEG signals of watching remaining part.
2) *Clip-based emotion recognition:* For each participant, four clips were used as the training set and the fifth clip was used for testing. The leave-one-clip-out cross validation was repeated five times and the average results were computed for each participant.

We compared these two results and gave possible explanations about difference between them. Our focus in this work is to discover the most effective EEG features for recognizing positive emotions. To do so, first, 150 well-known EEG features of frequency-band powers were extracted and collected as the pool of candidate features. Then, a linear regression and a nonlinear long short-term memory network (LSTM) were used as regressor, and ERC using LSTM as unit regressor produces the best results.

Last but not least, we made an extensive exploration of the proposed method. For one thing, we conducted the multi-target analysis based on both EEG and multimedia content features. The comparison could help us understand the effectiveness of EEG signal in emotion recognition. For the other, we investigated the neural correlates of five positive emotions (amusement, happiness, romance, tenderness and warmth). Our findings are expected to provide evidence towards the neural mechanisms of positive emotions from a novel multi-target perspective.

The remainder of this paper is organized as follows. In Section 2, we present the experimental procedure how to record EEG signals when individuals were watching these emotional materials. EEG data acquisition, data preprocessing, and feature extraction were also introduced in Section 2. Feature selection and machine learning algorithms were introduced in Section 3. Positive emotion recognition results were presented in Section 4. Major findings and conclusions were made in Section 5.

2 Method

2.1 Five Positive Emotional Film Clips

Five film clips from the standardized Chinese emotional film clips database [42] were used as the positive emotion stimuli in the present study. These five film clips with a highest success index in each emotional category aimed to elicit five positive emotional states respectively: amusement, happiness, romance, tenderness and warmth. Note that these five positive emotions were selected as representatives by considering the highest success index in emotional categories from more than one thousand Chinese movies evaluated by a relatively large population.

Amusement emerges when individuals appraise their current circumstances as involving some sort on non-serious social incongruity [17]. It was induced by a film clip from "*Just Another Pandora's Box*", which presents a humorous battle scene and last for 67 seconds in length. Happiness emerges when something that facilitates goal accomplishment happens or provides sensory pleasure [43]. Happiness was elicited by a 120-second clip from "*Jump ! Ashin*", which shows the happy scene after a hero's successful horse-vaulting. Romance emerges during the interactions between two lovers, and it was induced by a 91-second clip from *"The Myth"* describing a picture of the encounter between male and female heroes. Warmth emerges during the interactions between family members and it represents the family love. Warmth was elicited by a clip from *"Perfect Two"*, which shows the scene of father and son playing together and last for 60 seconds. Tenderness is defined as another kind of positive emotion related to love and attachment between individuals without intimacy. Tenderness was induced by a 99-second clip from "*A Simple Life*", which recalls the master's happy childhood accompanied by his servant.

All five selected film clips have lengths in 60-120 seconds and each clip contains 2-4 shots which have significantly different visual and auditory contents. The clips were displayed on 15-inch LCD screen and two stereo speakers were used to play sound at a comfortable level.

2.2 Participants

37 healthy undergraduate or graduate students (17 males and 20 females) were recruited in present study. Their ages ranged from 18 to 26 years old and the average age was 23.95 years (SD = 1.56 years). All of them were right-handed and had normal hearing, normal or corrected-to-normal vision. They were not allowed to ingest tobacco or caffeine 24 hours before the formal experiment. And all of them gave written informed consent after a detailed explanation of the experiment procedure in accordance with the Declaration of Helsinki. The current study was approved by the Ethics Committee of Human Experimentation at the Institute of Psychology, Chinese Academy of Sciences.

2.3 Formal Experimental Procedure

Upon arrival, an introduction of the experiment procedure was explained to participants prior to the formal experiment. The EEG recording system was set up and a Quik-Cap was put on the participant's head by two experimenters. Next, participants were instructed to sit straightly on the chair with a distance of 0.6 meters between eyes and the center of the screen. They were instructed to keep the body and head still and avoid obvious movements during EEG recording. They should also keep their chins on the chin strap during the formal experiment except for resting.

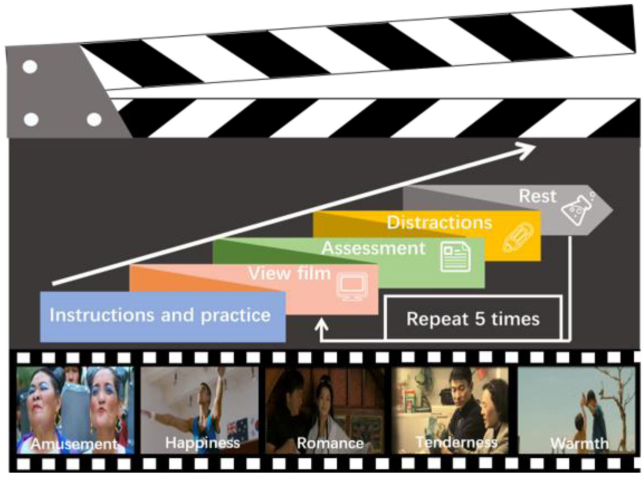

Fig. 1. The procedure of the formal experiment. Participants watched 5 movie clips depicting amusement, happiness, romance, tenderness, and warmth one by one, followed by a 10-item subjective assessment (five positive emotions: amusement, happiness, romance, tenderness, and warmth, five general experiences: valence, arousal, liking, familiarity, and dominance), a Go/NoGo distraction task, and a short break.

After these preparations, the participants performed two practice trials to get familiarized with the procedure. They watched two neutral film clips which were also selected from the standard Chinese emotional film clips database and accomplished the same subjective assessments as formal experiment. In the formal experiment, a 40-second Go/NoGo task [44] was shown to participants before each film clip in order to keep participants in a neutral affective state. Then one of five film clips were shown to participants. The presentation sequence of film clips was randomly arranged to keep a balance between participants. During the presentation of film clips, participants were instructed to watch carefully and immerse themselves in the film clips as if they were right in the scene. After the presentation of each film clip, participants were asked to rate their emotional experiences based on their true emotional feelings instead of their expected feelings on a 9-point Likert scales with 10 items, including ratings of five positive emotions (amusement, happiness, romance, tenderness, and warmth) as well as five general experiences (valence, arousal, liking, familiarity, and dominance). For example, after watching an amusing film clip, the participant may rate amusement 7 points, happiness 5 points, romance, tenderness, and warmth 2 points, respectively. Next, participants were arranged to take a rest for 80 seconds aiming to clear up their mind. The whole experiment lasted for approximately one hour, including 0.5 hours for EEG set up. The procedure of the formal experiment is shown in Fig. 1.

2.4 EEG Recording

The spontaneous EEG activity was recorded from 30 Ag/AgCl electrodes (Fp1, Fp2, F3, F4, F7, F8, Ft7, Ft8, Fc3, Fc4, T3, T4, C3, C4, Tp7, Tp8, Cp3, Cp4, T5, T6, P3, P4, O1, O2, Fz, FCz, Cz, CPz, Pz, and Oz). They were positioned in a 32-electrode Neuroscan Quik-Cap according to the international 10–20 system using a BrainAmp amplifier with a sampling rate of 1024 Hz. One of the electronically coupled mastoid electrodes was selected as a reference channel and the ground electrode was placed mid-forehead. Two horizontal and two vertical electrooculograms (EOGs) were recorded for identification of ocular artifacts using electrodes placed 10 mm away from the outer canthi of both eyes and below and above the left eye. Impedance was kept below 5 kΩ for all electrodes.

After recording, EEG data were digitally filtered with a 1-45 Hz bandpass using an open source Matlab toolbox called EEGLAB [45]. Then, an independent component analysis (ICA) was computed to decompose the EEG signals into independent components characterized by their topographies and PSDs. Features were visually and manually checked by experimenters. Each independent component was marked as either an EOG artifact or EEG signal component. The marked EEG signal components were reserved and back projected to reconstruct artifact-free EEG signals which were used for further feature extraction [46]. Whereas independent components marked as EOG artifact were removed with a mean rejection rate of 9.8% $(\mathrm{range} = 3.1 - 22.3\%)$. Next, EEG data were re-referenced to the average of the left and right mastoids.

2.5 Feature Extraction and Normalization

We followed the emotion recognition system in [46] to subdivide EEG signals into a number of 2-s time windows with a 50 percent overlap between two successive time windows. I.e., for an EEG signal of n seconds, it was subdivided into n$-$1 segments: each segment has 2 seconds and there is 1 second overlap between any two successive segments. After EEG signal segmentation, a fast Fourier transform (FFT), which is a classic technique to analyze a signal jointly in time and frequency and has been widely used in EEG signals processing [47], was applied to each segment.

For each positive film clip, the power of 5 frequency bands of EEG signals were extracted as EEG features from all 30 channels. These 5 frequency bands were: delta ($\boldsymbol{\delta}$: 1-4 Hz), theta ($\boldsymbol{\theta}$: 4-8 Hz), alpha ($\boldsymbol{\alpha}$: 8-13 Hz), beta ($\boldsymbol{\beta}$: 13-30 Hz), and gamma ($\boldsymbol{\gamma}$: 30-45 Hz). As a result, a total number of 150 EEG features were collected. For example, for each participant watching a 120-second film clip "*Jump ! Ashin*", the EEG signal was subdivided into 119 segment and for each segment, 150 EEG features were computed. As a result, for each participant, there were 119 sample data of happiness emotion and each data was of 150 dimensions. These 150 EEG features have been well studied in the literature of emotion recognition, which mainly focused on the differences between negative and positive emotions or the differences between negative emotions [46]. EEG feature normalization was composed of two sessions. First, the natural logarithm (log base e) of the features were calculated since most data were larger than 1. Second, the baseline power of each resting period before each clip was also averaged and subtracted from corresponding segments of the extracted features.

To eliminate the influence of video characteristics, MCA was performed to extract both visual and auditory features according to the DEAP dataset [48]. Similar to the EEG feature segments, the video stream was divided into a number of 2-s time windows with a 50 percent overlap between two successive time windows. Because each film clip has 25 frames per second, auditory features were calculated from and averaged on 50 frames in a 2-s time window. We used

TABLE 1
Visual and Auditory Features Extracted From Five Emotional Film Clips

Category	MCA Features
Visual (n = 52)	Lighting key
	20 bin color histogram of hue and lightness values
	Color variances
	Median lightness
	Motion Component
Auditory (n = 53)	13 MFCC coefficients, Derivative of MFCC, and Autocorrelation of MFCC
	Average energy of audio signal
	First five formants up to 5500Hz
	Time frequency feature, including MSpectum flux, Spectral centroid, Delta spectrum magnitude, and Band energy ratio
	First pitch frequency
	Average and standard deviation of zero crossing rate
	Proportion of silence ratio in a time window

Matlab to extract the lighting key and 20 bin color histogram of hue and lightness values in the HSV (hue, saturation, value) space, color variances in the international commission on illumination (CIE) luminance color space and median lightness in the HSL (hue, saturation, lightness) space. In addition, a Matlab toolbox BlockMatchingAlgoMPEG [49] was utilized to obtain motion components. For auditory analysis, we took out audio channels, encoding to mono MPEG-3 format at 44.1 kHz sampling rate. Then, MFCC, average energy, formant, time frequency feature, pitch, zero crossing rate and silence ratio were extracted with the librosa tool [50] on Python. Features were also averaged in each 2-s time window. Finally, there were 105 MCA features: 52 visual and 53 auditory features (see Table 1).

3 Positive Emotion Recognition Algorithms

3.1 Feature Selection

We collected 150 EEG features[1] and 105 MCA features as a pool of candidate features, which may contain irrelevant and redundant features for positive emotion recognition. We need to select a subset of features that are useful to build a good recognition model. Furthermore, for feature understanding, we also need to rank the selected features such that their contributions to emotion recognition can be evaluated.

Bending these two requirements in mind, we applied elastic net for feature selection and ranking. Elastic net is a linear model, combining lasso and ridge penalty functions together [51]. It is commonly used in feature selection and often outperforms the lasso [52]. Lasso penalty function penalizes the sum of absolute values of coefficients, and minimizing it will result in a subset of features to be zeros. Ridge penalty function penalizes the sum of squared values

1. These 150 EEG features have been widely studied to differentiate negative emotions from positive emotions, but have not been tested for the differences between multiple positive emotions.

of coefficients, and minimizing it will make the coefficients of all features close to zeros. For multi-target regression problems, the coefficients of elastic net model can be represented by a $\mathrm{m} \times \mathrm{k}$ weight matrix W of features, where m is the number of features and k is the number of targets. Here, the optimization function for elastic net is:

$$\frac{1}{2\mathrm{n}}\|T-FW\|_F^2+\alpha\mathrm{r}\|W\|_{2,1}+\frac{\alpha(1-\mathrm{r})}{2}\|W\|_F^2 \tag{1}$$

where M_F is the Frobenius norm of matrix M, and $M_{2,1} = \sum_i \sqrt{\sum_j M_{ij}^2}$ is the sum norm of each row. α is the penalty (or regularization) parameter while r controls the ratio between lasso and ridge penalties [53].

In our study, we used Sklearn on Python to implement elastic net algorithm, and set $\alpha = 0.1$ and $\mathrm{r} = 0.5$. Each discriminant vector $\mathrm{w_i}$ in matrix W assigns a multiple to each column in input data, i.e., a candidate feature in all samples, which reflects the influence factor of the corresponding feature in the recognition performance. The features corresponding zero elements in $\mathrm{w_i}$ are irrelevant or redundant, and the remaining features corresponding to non-zero elements in $\mathrm{w_i}$ play a role in recognition and could be ranked by the absolute value of these non-zero elements. Let

$$\mathrm{Q_i} = \sum_{j=1}^{m}|W_{ij}| \tag{2}$$

measure the influence factor for the i-th feature. According to Q , we sorted features for selection and analysis. In this paper, we selected 20 percent of original features which have the largest Q values.

In this paper, we used machine learning methods that trained models to predict percentage ratios of 5 positive emotions. This is a multivariate regression problem because it has several continuous values as outcomes, i.e., more than one dependent variable. The problem is a typical multi-target regression problem as we summarized in Section 1.1.3, which can be defined as finding a mapping model $M : F \rightarrow T$ that obtains the minimal prediction error, where F presents input space consisting of m feature vectors $F = [f_1,\ f_2, \ldots, f_m]$ and T is output space consisting of 5 target emotion ratio vectors $[t_1,\ t_2, \ldots, t_5]$. In Sections 3.2, 3.3, and 3.4, three models adopted from [41], [54] are used to deal with this problem.

3.2 Single-Target (ST)

ST treated each target separately–building five single, independent models for five targets. Each model M_i mapping from input space F to one target t_i, $\mathrm{i} = 1,\ 2,\ 3,\ 4,\ 5$. Final result was combined by outputs from each ST model.

3.3 Multi-Target Stacking (MTS)

MTS was introduced in Spyromitros-Xioufis, Tsoumakas, Groves and Vlahavas [41] to solve multi-target regression problem inspired from the stacked generalization idea applied in multi-label classification [55]. MTS not only considers independent mappings to each target, but also learns from the other targets to augment the mappings. Training MTS included two steps. In the first step, models M_i were trained as in ST. In the second step, these models were applied to obtain the prediction $T^P = [t_1^p, t_2^p, \ldots, t_5^p]$. Then the original input space F was augmented with T^P—for each target variable, the input space was expanded by the prediction of the other four target variables. For example, the input space for t_5 became $[f_1, f_2, \ldots, f_m,\ t_1^p, t_2^p, t_3^p, t_4^p,]$ in the second step. Five new models M_i' were trained and applied to obtain final output targets $T^{P'} = [t_1^{'p}, t_2^{'p}, \ldots, t_5^{'p}]$. Note that each target t_{i} is a ratio for regression instead of a label for classification.

TABLE 2
Parameters of LSTM Used in This Article

Layer number	2
Node number	Layer1: 100 Layer2: 50
Epoch number	30
Learning rate	0.01
Momentum	0.01
Batch size	20

3.4 Ensemble of Regressor Chains (ERC)

Similar to MTS, ERC also trains separate models like ST. But ERC chains ST regression models together, which is inspired by Classifier Chains that chains binary classification models [56]. Therefore, besides independent mappings for each target, ERC also considers reliance among targets. First, an order sequence for target variables was set. Second, models M_i were trained as in ST. Then for each target t_i, the original input space was expanded with the prediction of all target variables before it. For example, let the order be $[t_5, t_1, t_4, t_2, t_3]$, and the input space for t_2 became $[f_1, f_2, \ldots, f_m,\ t_5^p, t_1^p,\ t_4^p]$ in the second step. Five new models M_i' were trained and applied to obtain final output targets $T^{P'} = [t_1^{'p}, t_2^{'p}, \ldots,\ t_5^{'p}]$. Because chaining order affects prediction results, we randomly generated 5 different chains and calculated their average outputs as the final result.

In this paper, we chose two representative models, i.e., a linear regression, and a nonlinear LSTM as regressor. Linear regression tries to find a linear mapping with the lowest error, i.e., a straight line that can fit best through sample points. LSTM is an improvement of recurrent neural network (RNN), introducing a memory cell to preserve long-time state and learn long-term dependencies [57]. It has been widely used to process sequence data and achieve good performance [58]. In this paper, linear regression model was implemented with Sklearn [59] and LSTM was implemented with Keras [60], both on python. Parameters of LSTM were listed in Table 2. Varying lengths of 5 movie clips led to different lengths of feature sequences. We padded value $X_{\min} -1$ to the header of sequences, making all of them have the same length as that of the longest one, where $X_{\min}$ is the minimum value of input data. Then we used the masking layer to mask and identify padding from input sequences. If values of a sample time step are equal to $X_{\min}$ -1, it would be skipped in the network. It is worthy of noting that we used percentage as ratio values, i.e., target values range in [0,100].

3.5 Cross Validation

Two types of subject-dependent cross validation were performed:

- First, four-fold cross validation was applied for subject-dependent evaluation. Features extracted from EEG signals and video clips were divided into four equal-size subsets for each participant. At each time, one of the four subsets was used as the testing set and the other three subsets were used as the training set. The evaluation was repeated four times and the average results were computed.
- Second, we conducted clip-based emotion recognition, implemented by the leave-one-clip-out cross validation protocol. For each participant, four clips were used as the training set and the remaining one clip was the testing set. The cross validation was repeated five times and the average results were computed for each participant.

To check whether MCA features affect and help improve prediction results, we conduct experiments on EEG data, MCA data and combined EEG with MCA data.

To evaluate the prediction results, we calculated root mean squared error (RMSE) and Co-efficient of Determination (R^2). RMSE shows the differences between n prediction values y^p and ground truth values y^g:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{\left(y_i^p - y_i^g\right)^2}{n}} \tag{3}$$

Therefore, RMSE is a positive value and it measures the differences between predicted emotion targets and subjective assessments. A smaller RMSE means better performance, indicating that our predictions are closer to the actual values.

R^2 measures relative reduction of mean squared error using the prediction model, and the proportion of variance that the model can account for. $\overline{y^g}$ is average value of y^g.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i^g - y_i^p\right)^2}{\sum_{i=1}^{n} \left(y_i^g - \overline{y^g}\right)^2} \tag{4}$$

A positive value of R^2 means that the regression model outperforms the average baseline. And a better model generates a larger positive R^2. On the contrary, a negative value of R^2 means that the model produces worse results than baseline. Baseline is when all target emotions take the same ratio, i.e., 20 percent for each positive emotion in this study. Under this circumstance, $\mathrm{RMSE} = 10.348$ and $\mathrm{R}^2 = 0$.

4 Experimental Results

4.1 Subjective Assessment

Participants' subjective assessments (10 items: amusement, happiness, romance, tenderness, warmth, valence, arousal, liking, familiarity, dominance) were analyzed to examine statistical dependencies among five positive emotions. Differences in the subjective ratings of arousal and valence were compared, followed by the pairwise correlation between 10 subjective rating dimensions.

As shown in Fig. 2, the subjective rating of arousal were highest for the amusement eliciting video (M = 6.16, SD = 2.13), followed by the warmth eliciting video (M = 6.03, SD = 1.59), the happiness eliciting video (M = 5.24, SD = 2.17), the romance eliciting video (M = 5.51, SD = 1.63), and finally the tenderness eliciting video (M = 5.16, SD = 1.59). The subjective rating of valence for the videos were ranked as: warmth (M = 6.92, SD = 1.64), amusement (M = 6.13, SD = 2.35), happiness (M = 4.95, SD = 1.78), romance (M = 5.6, SD = 1.74), and tenderness (M = 4.97, SD = 1.92).

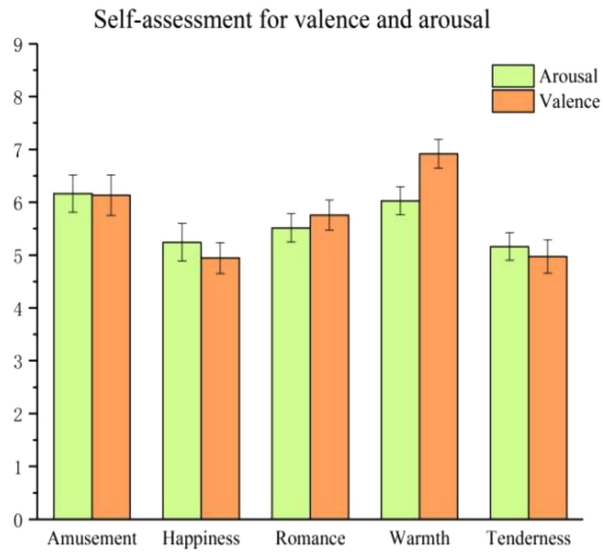

Fig. 2. Self-reported valence (orange bars) and arousal (light green bars) levels of five positive emotions (Error bars indicated ±1 standard errors).

Pairwise correlation coefficients between 10 subjective rating dimensions were shown in Table 3. Arousal was significantly related to happiness ($p < .001$), warmth ($p < .05$) and amusement ($p < .001$). Valence was significantly related to happiness ($p < .001$), warmth ($p < .001$), romance ($p < .05$) and amusement ($p < .001$). Liking was significantly related to all five positive emotions. Familiarity was significantly related to happiness ($p < .01$), warmth ($p < .05$), and romance ($p < .001$). Dominance was significantly related to happiness ($p < .05$) and amusement ($p < .05$). What's more, happiness, warmth, romance and amusement were moderately but significantly related to each other. Whereas tenderness was only significantly related to warmth ($p < .001$).

We note that the high correlation among positive emotions does not means that positive emotions are easily misjudged by participants. In our study, we chose the five positive emotion categories based on the research findings in [42], in which these emotions were selected by cluster analysis as representative discrete emotion labels. The selection in [42] acquired subjective ratings from a large population and more than one thousand Chinese movies, so that individual differences in emotion labelling had been reduced. That means the subjective feelings of these selected representative discrete emotion labels are highly distinguishable, even when participants experienced different positive emotions at the same time.

4.2 Five-target Regression of Positive Emotions

For four-fold cross validation, five-target regression model results were shown in Table 4. First, ERC using LSTM as unit regressor produced the best results, with lowest RMSE

TABLE 3
Pairwise Correlation Coefficients Between 10 Subjective Rating Dimensions

	1 arousal	2 valence	3 liking	4 familiarity	5 dominance	6 happiness	7 warmth	8 romance	9 amusement	10 tenderness
1	1									
2	.705**	1								
3	.636**	.834**	1							
4	.166*	.158*	.182*	1						
5	-.342**	-.178*	-.212**	-.005	1					
6	.588**	.783**	.712**	.192**	-.177*	1				
7	.183*	.328**	.473**	.175*	.056	.372**	1			
8	.110	.184*	.213**	.544**	.065	.243**	.343**	1		
9	.327**	.362**	.174*	-.122	-.168*	.308**	-.362**	-.161*	1	
10	-.024	.096	.174*	-.021	.125	.121	.421**	.058	-.105	1

*Note: **: Correlation is significant at the 0.01 level (2-tailed). *: Correlation is significant at the 0.05 level (2-tailed).*

TABLE 4
RMSE and R2 Obtained By Each Algorithms on EEG, MCA or EEG+MCA Features With/Without Feature Selection

		Single Target			Multi-target Stacking			Ensemble of Regressor Chains		
		EEG	MCA	EEG+ MCA	EEG	MCA	EEG+ MCA	EEG	MCA	EEG+ MCA
Linear Regression without feature selection	RMSE	11.128	19.783	17.957	19.103	19.185	19.523	20.478	19.107	17.262
	R^2	-0.296	-2.986	-2.295	-2.714	-2.734	-2.931	-3.490	-2.670	-1.925
LSTM without feature selection	RMSE	9.340	9.139	9.404	9.190	9.061	9.681	**8.325**	8.671	8.947
	R^2	0.161	0.217	0.146	0.155	0.231	0.046	**0.346**	0.297	0.235
Linear Regression with feature selection	RMSE	10.842	11.859	9.110	18.304	19.578	18.486	18.735	12.469	18.241
	R^2	-0.193	-0.342	0.162	-2.440	-2.892	-2.688	-2.477	-0.509	-2.346
LSTM with feature selection	RMSE	9.025	9.018	9.010	9.193	9.012	9.079	8.619	8.659	8.464
	R^2	0.237	0.239	0.238	0.206	0.224	0.224	0.306	0.299	0.330

As presented in Section 3.1, here the feature selection means that 20 percent of original features – which have the largest Q values in Eq. (2) – was selected for evaluation.

$= 8.325$ and highest $R^2 = 0.346$. The ERC+LSTM regression model could account for 34.6 percent subjective ratings of five positive emotions with 8.325 differences between predicted emotion targets and subjective assessments. Second, LSTM always performed better than linear regression, indicating its good ability to deal with sequence signals. Linear regression did not outperform the baseline since most $\mathrm{RMSE}_{\mathrm{LinearRegression}} > 10.348$ and $R^2 < 0$. Finally, using MCA features alone or fusing EEG features with MCA features did not bring better recognition results in most cases. Note that as described in Section 3.1, we sorted features according to Q values in Eq. (2) for feature selection and analysis. In particular, the feature selection in Table 4 means that we selected 20 percent of original features which have the largest Q values for evaluation. The results showed that

- Using feature selection, the performance of MCA or EEG+MCA can be improved, indicating that there are redundant features in MCA or EEG+MCA.
- For EEG features, LSTM without feature selection has the best performance, indicating that more than 20 percent original EEG features have effect on improving the performance.
- MCA+EEG performed worse than single MCA or EEG. One possible reason is that MCA+EEG has redundant and heterogeneous features which degrade the regression model performance than single MCA or EEG.

We also conducted clip-based emotion recognition, implemented by the leave-one-clip-out cross validation protocol. For each participant, four clips were used as the training set and the remaining one clip was the testing set. The cross validation was repeated five times and the average results were computed for each participant. To compare the results of two cross validation methods, we performed the same ERC+LSTM regression model on all EEG features (i.e., the best results in Table 4). The leave-one-clip-out cross validation achieved worse recognition performance (averaged RMSE $= 11.186$ and $R^2 = -0.298$ across all the participants) than the four-fold subject-dependent cross validation.

Since ERC algorithm using LSTM as base regressor obtained the best recognition results on EEG feature, further analyses were based on this configuration, i.e., ERC+LSTM on EEG features without feature selection. RMSE and R^2 of each participant were listed in Table 5. Individual RMSE results ranged from 7.134 to 9.506 (M $= 8.325$, SD $= 0.495$). Individual R^2 results ranged from 0.094 to 0.513 (M $= 0.346$, SD $= 0.083$). Our model achieved the best recognition performance for Participant 33 with RMSE $= 7.134$ and $R^2 = 0.513$, while the worst performance was gained for Participant 21 with RMSE $= 9.506$ and $R^2 = 0.094$. Fig. 3 showed the comparisons of predicted emotion targets for Participant 21 and Participant 33 with subjective ratings of five positive emotions, respectively. Obviously, better RMSE and R^2 results showed more centralized model predictions (i.e.,

TABLE 5
RMSE and R2 of 37 Participants Using ERC+LSTM Algorithm on All EEG Features

Participant	RMSE	R^2	Participant	RMSE	R^2
1	8.515	0.316	20	8.230	0.367
2	8.381	0.338	**21**	**9.506**	**0.094**
3	8.524	0.320	22	8.255	0.360
4	7.737	0.441	23	8.355	0.346
5	8.578	0.312	24	8.604	0.305
6	8.162	0.378	25	7.571	0.467
7	7.948	0.410	26	8.991	0.232
8	7.790	0.434	27	7.915	0.413
9	9.270	0.197	28	7.740	0.440
10	8.569	0.307	29	8.291	0.354
11	8.679	0.296	30	7.985	0.399
12	7.802	0.428	31	8.285	0.358
13	8.033	0.397	32	8.225	0.368
14	8.107	0.384	**33**	**7.134**	**0.513**
15	8.386	0.338	34	8.787	0.259
16	8.099	0.390	35	8.935	0.258
17	9.398	0.168	36	8.156	0.382
18	8.349	0.344	37	8.272	0.360
19	8.467	0.328			

smaller ranges of predicted values in blue) and subjective assessments were closer to the predictions (i.e., shorter distances between red stars and blue dots).

We also converted percentage values to ranking numbers. The emotion taking the highest percentage of all five targets ranks at No.1, the second highest at No.2 and so on. Then Kendall rank correlation coefficient were calculated for each prediction to measure the rank correlation:

$$\tau = \frac{p_c - p_d}{n(n-1)/2} \tag{5}$$

where p_c represents number of concordant pairs and p_d is the number of discordant pairs, $p_c + p_d = n(n-1)/2$. Kendall rank correlation coefficient ranges in $[-1, 1]$. If $\tau > 0$, two ranks are similar, and larger value indicates better agreement between ranks. If $\tau = 0$, then two ranks are independent. $\tau < 0$ indicates that there is disagreement between ranks, and lower value indicates more dissimilarity. In this study, Kendall rank correlation coefficients were averaged across all participants and 4 folds. Consistent with the RMSE and R^2 results, ERC algorithm using LSTM as base regressor achieved the best Kendall rank correlation coefficient, 0.165, on all EEG features without feature selection. The averaged Kendall rank correlation coefficients were 0.068 for ST and 0.12 for MTS, respectively.

4.3 Neural Representation of Positive Emotion

In Table 4, the results showed that the ERC+LSTM regression model on all EEG features achieved the best five-target recognition performance. To differentiate the contribution between EEG and MCA features and the contribution within EEG features, we performed ERC algorithm using LSTM as base regressor on both EEG and MCA features with feature selection and ranking described in Section 3.1. Then, we counted the total times from all folds of all participants when each feature was selected. We found that the top 7 features were all extracted from the alpha frequency band of EEG signals at CP4, C4, P3, C3, P4, FC3 and CP3 electrode sites. The best rank among all 105 MCA features was at No. 98. In other words, the top 97 features were the

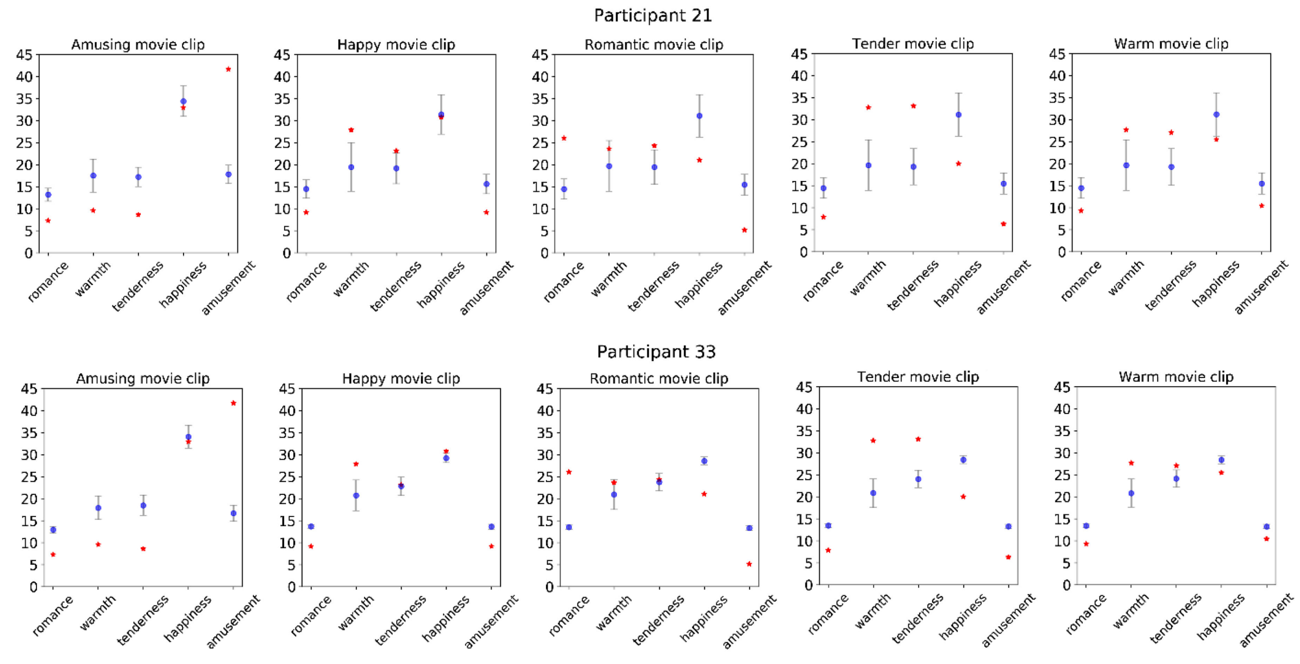

Fig. 3. Comparisons of predicted emotion targets for Participant 21 (upper panel) and Participant 33 (lower panel) with subjective ratings of five positive emotions. Each figure shows the comparison when the participant watches an emotional (amusing, happy, romantic, tender, and warm) film clip. X-axis represents five corresponding positive emotions (amusement, happiness, romance, tenderness, and warmth). Blue dots and ranges (mean ±1 standard deviation) indicates the predicted percentage of each positive emotion made by our algorithm averaged across a number of time windows described in Section 2.5. Red star indicates the self-reported percentage of each positive emotion (a single point in each emotional category).

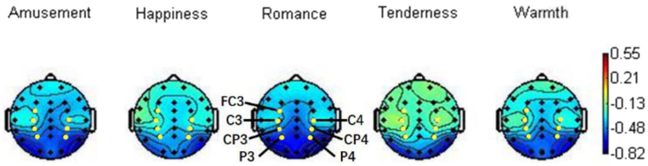

Fig. 4. The topographies of normalized power in the alpha frequency band (8-13 Hz) for each category of five positive emotions. Electrode sites of top 7 features are marked in yellow.

power spectral density of EEG signals, indicating better contribution and importance of EEG features in the recognition of positive emotions than MCA features.

The top features from EEG electrodes at the central sulcus and posterior parietal (CP4, C4, P3, C3, P4, FC3 and CP3) were symmetrically distributed along the midline (i.e., CP3- CP4, C3- C4, and P3- P4 appeared in pairs, see Fig. 4), and the alpha frequency band of EEG signals contributed more in the regression model fitting than delta, beta, theta or gamma frequency band, which showed a unique and symmetric characteristic of the alpha frequency band in representing five positive emotions.

To see the changes of EEG activities during watching each film clip, we computed the average alpha band PSD at CP4 site (i.e., the feature with the greatest contribution to positive emotion recognition) every 10 second from the beginning to the end of each film clip. For example, the amusing film clip lasted for 61 second, then 6 time points were extracted. The first time point calculated the average alpha band PSD at CP4 site from the 1st to the 10th second. Then, repeated measures ANOVAs were performed with the time point as a within-subjects variable for each film clip.

For amusement, the main effect of time point was significant ($F(5,175) = 2.98$, $p = .033$). The post hoc effect analysis revealed that the average alpha band PSD from CP4 site at the 4th ($p = .018$) and 5th time point ($p = .005$) were significantly higher than the 2nd time point. The average alpha band PSD from CP4 site at the 4th ($p = .019$) and 5th time point ($p = .007$) were also significantly higher than the 6th time point. The main effect of time point was also significant for happiness ($F(7,245) = 32.44$, $p < .001$), romance ($F(6,210) = 28.45$, $p < .001$), tenderness ($F(8,272) = 37.45$, $p<.001$), and warmth ($F(7,245) = 25.52$, $p < .001$). The post hoc effect analysis revealed that the average alpha band PSD from CP4 site at both the 7th and 8th time point were significantly higher than that at the other time points ($ps < .001$) for happiness. The 7th time point was significantly higher than the other time points ($ps < .001$) for romance. The last three time points were significantly higher than the first five time points ($ps < .001$) for tenderness. The last two time points were significantly higher than the first six time points ($ps < .001$) for warmth.

4.4 Discussion

There are two major contributions of the current study. First, regression-based methods were utilized to predict correlated positive emotional states using EEG signals which achieved good results. Second, feature selection algorithm was applied to select features that contribute most to the regression and explore the possible neural representation of five positive emotions.

It probably goes without saying that various positive emotion categories are difficult to induce via film clips compared with some typical positive (e.g., amusement and happy) and negative (e.g., anger, sad and fear) categories. And the subjective feelings of film-induced different positive emotions are highly correlated according to the results of correlation analysis, which is consistent with previous studies [28]. Thus, both linear regression and long short-term memory network were used as regressors to predict the proportion of five emotional categories using both EEG and MCA features. Nonlinear regressor with EEG features only had the best prediction effect, which could provide two enlightenments.

On the one hand, multi-target regression prediction for five emotional categories simultaneously is more consistent with a non-linear problem, and more nonlinear regressors can be considered in further study to improve the result of regression. On another, compared to music-induced emotion recognition modeled as a multi-label classification problem, EEG features were the most effective features in predicting individual's emotional states rather than basic physical properties of videos due to both results of regression and Kendall rank correlation. This also reflects the high ecological validity of our video database, since different film clip has different MCA features which had little contribution to recognition results. And the difference between five film clips were more likely emotional. What's more, according to RMSE and R^2 of 37 participants, there are still big differences between individuals. The possible explanation is that the experience of positive emotions (both behavioral and physiological) are largely depends on individual differences. Further multi-target emotion recognition using EEG signals can be carried out at the individual level.

In this study, the proposed multi-target regression model achieves good results on using the EEG signals of one part of a film clip to predict positive emotions of another part of the same film clip. However, the clip-based cross validation achieved worse recognition performance than the four-fold subject-dependent cross validation. One possible reason was that each video clip was expected to elicit a stronger target emotion compared to the other four positive emotions. The target emotion as well as the proportion of target emotion to the other four non-target emotions of the training clips was different from that of the testing clip. Therefore, it was difficult for the regression model to apply the learned distribution of five positive emotions in detecting another pattern of the same five emotions.

Additionally, the most predictive features for recognizing different positive emotions in our study were obtained from the alpha frequency band, and this result is in line with previous studies indicating that the alpha band is suitable for EEG-based emotion classification, which has proven to be sensitive to emotional changes [61]. Based on the results of previous studies, frontal alpha asymmetry (FAA) which reflect the asymmetric brain activity in the frontal cortex (such as relatively low or high activity in the right hemisphere compared to left hemisphere) is a typical neural indicator of valence [62], [63]. It was reported that tenderness was associated with lower alpha power in the left hemisphere than the right hemisphere and anger was associated with higher alpha power in the left hemisphere than the right hemisphere at FP1/FP2 and F3/F4 sites [61]. As for the positive emotions, similar result of symmetrical alpha power was found at F3 and F4 sites to recognise tenderness and amusement. In the present study, similar symmetrical alpha band pattern was found at the central sulcus and posterior parietal (CP4, C4, P3, C3, P4, FC3 and CP3), which provided a possible explanation that EEG features sensitive to positive emotional responses are also symmetrical distributed alpha band features. However, these symmetrical distributed alpha band features aiming to represent similar positive emotions are more posterior than FAA that used to distinguish between positive and negative emotions.

To sum up, regression algorithm is used for the first time in the current study to solve the problem of multi-target recognition of different positive emotions using EEG signals. And some important features such as alpha band were found to represent different positive emotional states which were highly correlated with each other.

5 Conclusion

The present study systematically investigated the contribution of EEG features for positive emotion recognition. Both EEG and MCA features were recorded and extracted. The ERC+LSTM regression model on all EEG features merely produced the best regression results for the five-target positive emotion recognition (i.e., the lowest RMSE and the highest R^2) and the best Kendall rank correlation coefficient. And the elastic net selected the top 7 ranked features (alpha band activities) which contributed most in regression. Our results provide evidence to guide practical application of recognizing highly-correlated positive emotions using EEG features.

Acknowledgments

This work was supported by the National Natural Science Foundation of China under Grants 31771226, U1736220, and 61725204.

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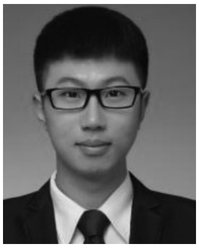

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