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Estimating Human Response to Taste using EEG

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Abstract— **In order to implement affective computing, there have been several studies to elicit human emotion using audio and video stimuli or by recalling previous events. Taste-elicited emotion has also been investigated using food to induce different levels of pleasure. This is monitored using a range of methods, from questionnaire feedback to electrophysiological responses of autonomic nervous system (ANS) and central nervous system (CNS). In this work, we establish that emotions elicited by taste can be monitored using electroencephalogram (EEG), and, for rigour, compare the response to a taste stimulus against the response to the recall of the same taste. The character of emotions were assessed using a subjective measurement, the hedonic score, which describes the pleasant or unpleasant moods of subjects in response to each taste. The classification performance of EEG responses shows excellent separability between the different emotions induced by different tastes. In addition, it is shown that emotion elicited by taste recall is stronger than the stimulus-elicited emotion.**

I. Introduction

Recently, studies which aim to detect and model human emotions have received considerable attention in order to implement reliable affective computing [1], [2]. Affective computing is a computer or computer-based technology which has the ability to understand affective states of users, such as satisfaction, confusion, frustration or amusement [3]. Such feedback then provides interactive services to the users, depending on their emotional states.

In an effort to model human communication, several studies to recognize emotions from facial expression and voice have been reported. For instance, speech signals which contained emotional information were classified in [4] and they showed that a classification performance close to human performance was possible. Chen et al. [5] reported 80-90% classification accuracy for facial expressions using pattern recognition algorithms. Another study reports that spontaneous reactions, when the affective states change, can be detected using distinct facial electromyography (EMG) on emotion-relevant facial muscles [6]. The changing autonomic nervous system (ANS) responses associated with emotions were reported using several biosignals, for example skin temperature, skin conductance, respiration and heart rate [7], [8].

In recent years EEG signals originating from the central nervous system (CNS) has interested the researchers of brain computer/machine interfaces (BCI/BMI) [9]. EEG signals are expected to provide true emotional information which is elicited at the unconscious level of the subject even if the subject tries to control his affective state. For instance, Michela et al. [10] and Kislova et al. [11] showed a relationship between observed EEG and emotions elicited by video and voice.

The hypothalamus in the brain is responsible for processing incoming signals and triggering the corresponding ANS effects which can then be observed, for instance, as increasing heart rate or galvanic skin response [12]. The hypothalamus passes the stimuli information to the amygdala in the subcortical, which plays a primary role in connecting stimuli to emotional reactions and to assess of the stimuli by matching them with past experiences. These physiological phenomena reflect the relationship between ANS and CNS for emotional states. There is neuroimaging evidence which shows a co-occurrence of activation in cortical (frontal, insular and anterior temporal), subcortical (amygdala, thalamus and hypothalamus), and midbrain structures and increased SCR and HR during pleasant and unpleasant emotional states [13], [14]. Waldstein et al. [15] illustrated that positive correlations exist between left and right midfrontal cortical activation and heart rate (HR) when subjects recalled angry experiences. Rutkowski et al. [16] discriminated between patterns of neurophysiological signals, together with electrophysiological data such as electrocardiogram (ECG) and electrooculogram (EOG), in response to emotional stimuli.

When we taste a food, a gustatory stimulus by sensing a taste evokes a response, discriminative at the cortical level and affective (emotional) at the hypothalamo-limbic level [17]. The affective or hedonic dimension corresponding to the amount of pleasure or displeasure determines approach or avoidance to a food. Apart from the hedonic score, there were several established methods to estimate this affective response. Rousmans et al. [18] tried to monitor the periphery electrophysiological changes with primary tastes, while Fox et al. [19] investigated CNS responses to tastes by monitoring EEG of newborn infants when they were given sucrose and citric acid solution.

In this work, we expand the study of taste-elicited emotion by investigating its effect on EEG. For rigour, we also analyse the strength of the response to the same taste when recalled from memory. In the experiment, healthy subjects were asked to taste a wide range of foods/liquids and asked to provide relevant emotional feedback on the taste. Consistencies were observed between patterns in the EEG and responses to tastes. We also found that the same EEG patterns were elicited when the subjects were asked to recall their taste experiences.

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II. Taste Experiments

A. Subjects

Seven volunteers (6 males and 1 female) were recruited to take part in the study. The mean age was 30 years, ranging from 28 to 37, and no subjects reported any gustatory disorder. They were requested to abstain from eating or drinking anything (except water) 2 hours prior to the experiment.

B. Taste stimuli

Taste stimuli were a solution of 0.3M sucrose, 4g of milk chocolate as a pleasant stimulus and a solution of 0.15M NaCl and 2g of mustard as an unpleasant stimulus. Drinking water (pH = 7.0) was used as a neutral stimulus (baseline) and was also used to rinse the mouth of subjects after each trial. Rousmans et al. [18] used the solutions of sucrose and NaCl to elicit pleasant and unpleasant emotions. Milk chocolate was chosen because of its high sugar content and because it is widely agreed that it is enjoyable to eat. Mustard was used due to its bitter taste. The emotional reactions of the subjects to all the taste stimuli were recorded in a questionnaire according to the hedonic scale with a score varying from 0 to 10; 0 = 'I like very much (highly pleasant)', scale 5 = 'neither pleasant nor unpleasant (neutral)' through to scale 10 = 'I don't like at all (highly unpleasant)' [18].

C. Procedure

The subjects participated in a test session lasting about 1 hour. They were seated in a comfortable chair and were verbally informed about the procedure. The subjects began the test with drinking water followed by a NaCl solution, mustard, drinking water, sucrose solution and milk chocolate. During the trials, they did not swallow the liquid or food, but kept them in their mouths for 8s with their eyes closed. After 8s of EEG recordings, they spat the solution out and rinsed their mouths with drinking water. After each trial, the subjects filled out the hedonic scale questionnaire to evaluate their emotional response. This experimental procedure was repeated five times for the five different taste stimuli.

After the experiments, the subjects took a break for 10 minutes and began the emotion recall test. In this session, the subjects opened their eyes and were shown the taste stimulus for 8s while their EEG response was recorded. During the 8s recording, they were requested to recall their feelings when they tasted the stimulus. This experiment was also repeated five times for the five recalling tests in a sequence of drinking water, NaCl solution, mustard, sucrose solution and milk chocolate.

D. Data Acquisition

The EEG data was recorded at positions AF7, AF8, F3, F4, T7 and T8 according to the 10-20 system [20] and was sampled at 256Hz. All emotions share the areas: prefrontal cortex, cingulate gyrus and temporal cortex [21], [3]. Recordings were made with reference to the right earlobe, and amplified and bandpass filtered at 0.5-100Hz using a g.MOBIlab+ portable biosignal acquisition system. The data were bandpass filtered again to isolate the alpha (8-13Hz), beta (13-30Hz) and gamma (35-45Hz) bands, using a fifth-order Butterworth band-pass filter. Delta (1-3Hz) and theta (4-7Hz) bands were ignored [22].

E. Common Spatial Pattern (CSP)

Signal features relevant to the emotions were extracted using CSP, a standard feature extraction technique in BCI applications [23], [24]. It determines spatial filters that maximise the variance of signals of one class and simultaneously minimise the variance of signals of the other class.

An 8s EEG data from the training set was segmented into 2s segments and a single segment was represented as an $N \times T$ matrix $\overline{\mathbf{X}}$, where N is the number of channels and T is the number of samples per channel. The normalised spatial covariance of $\overline{\mathbf{X}}$ can be calculated from

$$C = \frac{\overline{\mathbf{X}}\overline{\mathbf{X}}^T}{tr(\overline{\mathbf{X}}\overline{\mathbf{X}}^T)} \tag{1}$$

where $(\cdot)^T$ denotes the matrix transpose operator and $tr(\mathbf{X})$ is the trace of $\mathbf{X}$. The spatial covariances $\overline{\mathbf{C}}_{d\in[a,b]}$ for two different mental tasks, a and b, are obtained by averaging the trials of each task. The CSP analysis seeks to find a matrix $\mathbf{W}$ and diagonal matrices $\mathbf{\Lambda}_a$ and $\mathbf{\Lambda}_b$ ($\mathbf{\Lambda}_a$+$\mathbf{\Lambda}_b$ = $\mathbf{I}$, identity matrix) with elements $d \in$ [a,b] such that

$$\mathbf{W}^T\overline{\mathbf{C}}_a\mathbf{W} = \mathbf{\Lambda}_a,\ \mathbf{W}^T\overline{\mathbf{C}}_b\mathbf{W} = \mathbf{\Lambda}_b \tag{2}$$

This can be achieved via the following process. The composite spatial covariance is given as

$$\mathbf{C}_c = \overline{\mathbf{C}}_a + \overline{\mathbf{C}}_b \tag{3}$$

where $\mathbf{C}_c$ is factored as $\mathbf{C}_c = \mathbf{U}_c\mathbf{\Lambda}_c\mathbf{U}_c^T$, $\mathbf{U}_c$ is the matrix of eigenvectors, and $\mathbf{\Lambda}_c$ is the diagonal matrix of eigenvalues, which are sorted in the descending order. Using the whitening transformation, $\mathbf{P} = \sqrt{\mathbf{\Lambda}_c^{-1}}\mathbf{U}_c^T$, the variances in the space spanned by $\mathbf{U}_c$ are equalised, which make all eigenvalues of $\mathbf{P}\mathbf{C}_c\mathbf{P}^T$ equal to 1. Let $\mathbf{S}_a = \mathbf{P}\overline{\mathbf{C}}_a\mathbf{P}^T$ and $\mathbf{S}_b = \mathbf{P}\overline{\mathbf{C}}_b\mathbf{P}^T$, and then $\mathbf{S}_a$ and $\mathbf{S}_b$ share the common eigenvector matrix, i.e.,

$$\mathbf{B}^T\mathbf{S}_a\mathbf{B} = \mathbf{\Lambda}_a,\ \mathbf{B}^T\mathbf{S}_b\mathbf{B} = \mathbf{\Lambda}_b,\ (\mathbf{\Lambda}_a + \mathbf{\Lambda}_b = \mathbf{I}) \tag{4}$$

Since we assume the eigenvalues in this paper are sorted in descending order, the final spatial filter that satisfies (2) is given by

$$\mathbf{W} = \mathbf{B}^T\mathbf{P} \tag{5}$$

Using this, the EEG signals in the training and test sets are projected as

$$\mathbf{Z} = \mathbf{W}\mathbf{X} \tag{6}$$

Each row vector $\mathbf{w}_j$ (j = 1, …, N) of $\mathbf{W}$ denotes a spatial filter.

F. Classification

The classification performances for pairs of emotional tasks were examined and are shown in Table I and II. For discrimination between two responses, a small number (m = 1) of variances from the spatial filtered signals using eq. (6) were used for feature extraction. The signal $\mathbf{z}_p$ ($p = 1, \ldots,\ m$ and $N - m + 1, \ldots,\ N$) from $\mathbf{Z}$ that maximise the difference of variance between two groups are associated with the largest eigenvalues contained within $\mathbf{\Lambda}_a$ and $\mathbf{\Lambda}_b$.

TABLE I

THE CLASSIFICATION PERFORMANCE FOR THE TASTE-ELICITED EMOTION COMBINATIONS (SUCROSE (SU), NACL (NC), MUSTARD (MT), MILK CHOCOLATE (MC), WATER 1 (WT1) AND WATER 2 (WT2)). NOTE THAT THE MEAN CLASSIFICATION ACCURACIES OF FIVE SUBJECTS EXCEED 70%.

Stimulus \ Subject	A	B	C	D	E	F	G
SU-NC	73.8	59.8	64.6	59.8	86.0	81.7	67.1
SU-MT	76.6	88.2	68.8	77.6	100	65.6	81.8
MC-NC	72.8	98.7	59.7	79.3	76.8	71.9	76.9
MC-MT	80.6	61.8	69.7	51.4	100	80.3	65.3
SU-WT1	76.6	91.6	47.2	52.1	84.1	65.2	53.5
SU-WT2	79.3	44.8	64.0	46.8	57.2	64.3	78.8
MC-WT1	53.5	93.6	59.1	67.9	91.7	78.2	78.3
MC-WT2	67.9	90.4	69.3	68.8	79.9	58.8	81.5
MT-WT1	86.4	59.8	65.5	56.3	100	86.3	62.2
MT-WT2	95.9	78.3	59.6	94.4	100	78.7	72.5
NC-WT1	81.8	74.1	54.4	66.3	83.3	69.6	61.3
NC-WT2	89.2	54.2	59.1	78.8	88.4	75.7	85.1
MEAN	77.9	74.6	61.8	66.6	87.3	73.0	72.0
MAX	95.9	98.7	69.7	94.4	100	86.3	85.1

TABLE II

THE CLASSIFICATION PERFORMANCE FOR THE RECALL-ELICITED EMOTION COMBINATIONS (SUCROSE (SU), NACL (NC), MUSTARD (MT), MILK CHOCOLATE (MC) AND WATER (WT)). NOTE THAT THE MEAN CLASSIFICATION ACCURACIES OF ALL SUBJECTS EXCEED 70% AND FIVE SHOW HIGHER SEPARATION RATES THAN THOSE OF TASTE-ELICITED EMOTION.

Stimulus \ Subject	A	B	C	D	E	F	G
SU-NC	61.8	66.4	90.2	63.2	82.7	86.8	80.5
SU-MT	66.3	58.1	52.2	56.6	71.3	60.0	89.8
MC-NC	100	62.9	74.6	84.8	100	77.0	96.2
MC-MT	83.3	63.8	84.6	76.8	100	91.6	62.3
SU-WT	84.5	98.5	76.8	53.7	80.4	100.0	69.8
MC-WT	100	90.8	97.3	94.0	100	93.9	75.4
MT-WT	90.0	89.5	86.7	76.0	65.7	100.0	87.8
NC-WT	64.0	62.2	72.9	63.3	47.9	82.4	79.3
MEAN	81.2	74.0	79.4	71.1	81	87.5	80.1
MAX	100	98.5	97.3	94.0	100	100	96.2

These signals are the m first and last rows of $\mathbf{Z}$ due to the calculation of $\mathbf{W}$

$$f_p = log(\frac{var(\mathbf{z}_p)}{\sum_{i=1}^{2m} var(\mathbf{z}_i)}) \tag{7}$$

The feature vectors f_p were supplied to a classifier, a support vector machine (SVM) [25] with Gaussian kernel (code obtained from [26]). The combination of two emotions had 40 samples of 2s segment data because in the recording each subject had 5 trials for an emotion task and the length of each EEG data was 8s long. The numbers of training sets and test sets were respectively 28 and 12. The classification was repeated 100 times while mixing the sample order (100 $\times$ cross-validation), and the final classification result was the average of these outcomes.

III. CLASSIFICATION RESULTS

The subjective evaluations, using the mean hedonic scores (HS) across the subjects, were different among the five tastes. The milk chocolate and sucrose solution were rated as the most pleasant stimuli (HS = 0.49 $\pm$ 0.68 and HS = 2.09 $\pm$ 0.82 respectively). The NaCl solution (HS = 8.03 $\pm$ 0.89) and mustard (HS = 8.43 $\pm$ 1.34) were rated as unpleasant and very unpleasant respectively. Drinking water (HS = 5.03 $\pm$ 0.38) was rated neither pleasant nor unpleasant.

TABLE III

THE CLASSIFICATION PERFORMANCE FOR THE TASTE-ELICITED EMOTION GROUPS (PLEASURE (P), DISPLEASURE (D) AND NEUTRAL (N)). IT IS SHOWN THAT A GROUP OF EMOTIONAL TASTES CAN BE CLASSIFIED FROM OTHER EMOTIONAL TASTE GROUPS.

	A	B	C	D	E	F	G	MEAN
P-D	62.3	68.3	61.0	53.1	85.4	66.6	58.3	65.0
P-N	63.3	83.0	56.5	56.0	76.2	67.8	64.5	66.8
D-N	84.8	53.5	49.1	69.1	94.2	81.9	56.0	69.8
MEAN	70.1	68.3	55.5	59.4	85.3	72.1	59.6	

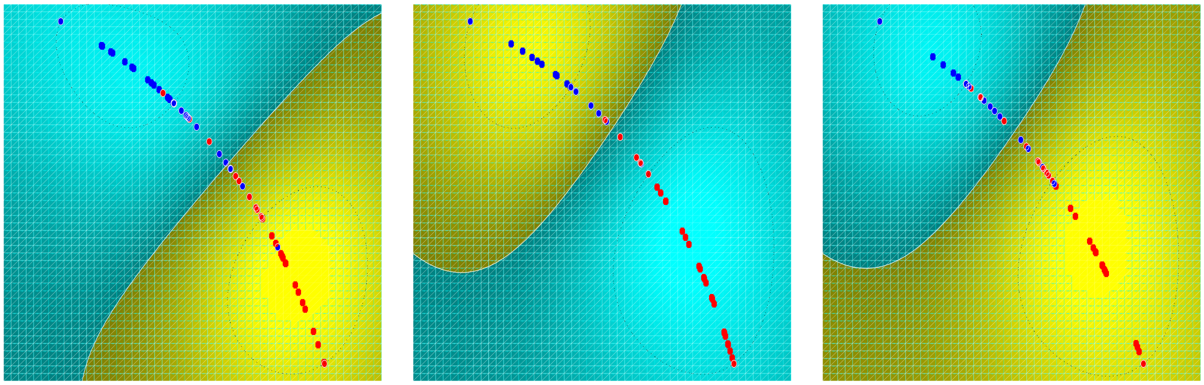
TABLE IV

THE CLASSIFICATION PERFORMANCE FOR THE RECALL-ELICITED EMOTION GROUPS (PLEASURE (P), DISPLEASURE (D) AND NEUTRAL (N)). NOTE THAT SIX SUBJECTS SHOW HIGHER CLASSIFICATION ACCURACIES THAN THOSE OF TASTE-ELICITED EMOTIONS.

	A	B	C	D	E	F	G	MEAN
P-D	79.3	55.2	67.0	57.7	79.8	62.8	66.8	66.9
P-N	86.9	92.7	91.3	52.8	81.3	89.1	79.9	82.0
D-N	72.0	84.9	92.4	78.4	64.3	87.3	75.2	79.2
MEAN	79.4	77.6	83.6	63.0	75.1	79.7	74.0	

Table I shows the classification performances for 12 combinations of two different tastes, which were grouped into three categories (pleasant, unpleasant and neutral tastes) based on the hedonic score. On average, five subjects among seven achieved classification accuracy exceeding 70%, and subject E obtained the highest average rate of 87.3%. The classification results of the taste recall tests are shown in Table II, where there was one 'water' session while taste experiment had two neutral stimulus sessions, 'WT1' before the unpleasant tastes and 'WT2' before the pleasant tastes. All subjects obtained average classification accuracies exceeding 70% and four were higher than 80%. Compared to the taste experiment results in Table I, all subjects except B and E achieved higher classification rates in these recall tests. It is also noted that seven cases of all considered scenarios in Table II show perfect separation between two classes with 100% accuracy.

The classification accuracies were calculated among the groups of pleasant, unpleasant and neutral tastes in Table III and IV, that is, sucrose solution and milk chocolate were combined in a pleasant group and NaCl solution and mustard were combined in an unpleasant group. From this analysis, only the pleasant and unpleasant emotion responses from the stimuli and recall, not an individual taste response, can be examined. Fig. 1 shows the two features of the recall test data of subject A obtained using CSP - with the first feature on the X-axis and the second feature on the Y-axis. As can be seen, the features of two different emotions make two separable groups even if each group is composed of two different taste stimuli. Meaningful classification performances for all subjects are shown in Table III and IV. Similar to the results in Table I and II, the responses of recall tests had 12% higher classification accuracy than those of taste tests across all



(a) Pleasure (blue) vs Displeasure (red) (b) Pleasure (blue) vs Neutral (red) (c) Displeasure (blue) vs Neutral (red)

Fig. 1. Features of the recall test for subject A. Dots in the white circles are support vectors. Note that two different emotional responses are separable in the feature space.

subjects except subject E. These results suggest that emotion responses elicited by recalling tastes are stronger than those elicited by the actual taste in terms of classification performance.

IV. Conclusion

We have investigated EEG responses to taste stimuli, and have established that it is possible, with high accuracy, to differentiate between the responses using features based on common spatial patterns. The emotions induced by memory recall to pleasant and unpleasant taste stimuli were also analysed and results were consistent with those based on the response to the actual taste. Future work will combine EEG features with physiological responses.

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