P200 and N400 Induced Aesthetic Quality Assessment of an Actor Using Type-2 Fuzzy Reasoning

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***Abstract*— The paper introduces a novel technique for aesthetic quality assessment of an actor from her/his audio-visual clips using the acquired P200 and N400 EEG-responses of the experimental subjects. The P200 signal responds with high amplitude when the subject experiences a non-beautiful stimulus, whereas the N400 signal offers a high negativity for good tonal quality of the actor in the audio-visual stimulus. The synergy of small P200 amplitude and large N400 negativity jointly indicates good aesthetic quality of the actor present in the audio-visual stimulus. The intra/inter-subjective variations in the assessment of aesthetic quality are resolved using a General Type-2 Fuzzy Reasoning. The novelty of the present research lies in the design of the General Type-2 Fuzzy Reasoning algorithm for assessment of aesthetic quality from the measurement of peak power and total power in the selected band of the above two signals. Experiments undertaken confirm that the proposed technique outperforms the state-of-the art techniques when realized for the present application. Finally, the top-ranking stimuli are identified based on the average score of the aesthetic quality of the stimuli assessed by 30 subjects. The top-ranking stimuli may be utilized for psychological nourishment of mentally-challenged people. Statistical technique undertaken confirms the superiority of the proposed technique with its competitors.**

Keywords— Aesthetic quality assessment, P200 signal, N400 signal, Type - 2 fuzzy reasoning, General Type- 2 fuzzy reasoning.

I. Introduction

Aesthetic quality is often used in the context of beauty, appreciation of beauty and/or pleasant appearance of a person [1]. Apart from beauty, the phrase: 'pleasant appearance' includes tonal qualities, personality, and many other silent but artful person-specific attributes [2]. Presence of a beautiful person with respect to physical attributes and/or tonal quality is important for psychological nourishments of people, particularly those suffering from psychological disorder/melancholy/lack of confidence, and the like [3]. This paper proposes a novel Brain-computer Interface (BCI) technique to assess the aesthetic qualities of actors in audio-visual stimuli by a number of (human) subjects. Here, the P200 signal is utilized to classify the subject's assessment about the appearance of a beautiful face [4], [5] in the stimuli. It is indeed important to mention here that the P200 signal is released from the Parietal lobe with a large peak around 200 ms away from the onset of a non-beautiful face stimulus [6]. The N400 signal, on the other hand, is released when the subject experiences rhythmic, meaningful and congruent words [7]. A combination of absence of P200 and presence of N400 signal indicates high degree of aesthetic quality of the Audio-visual stimulus presented to a subject.

The paper attempts to assess the degree of aesthetic quality of an actor, present in an audio-visual stimulus, by decoding the presence/absence of the above two Event Related Potential (ERP) acquired from the brain of experimental subjects. The intra/inter-subjective variations in the assessment of aesthetic quality appears as a source of uncertainty, and is resolved here using a General Type-2 Fuzzy Reasoning [8], [9], [10].

Type-2 fuzzy set has shown remarkable success in handling uncertainty in decision-support systems [11]. Two variants of type-2 fuzzy sets are widely used for uncertainty management in multi-session experimental data. They are popularly known as General Type-2 Fuzzy Sets (GT2FS) [12] and Interval Type-2 Fuzzy Sets (IT2FS) [13]. An IT2FS is usually represented by two membership functions, called Upper Membership Function (UMF), and Lower Membership Function (LMF). The space lying between the UMF and the LMF is called the footprint of uncertainty (FOU) [14]. The FOU includes all possible type-1 membership functions and thus provides users the freedom of representing uncertainty due to intra- and/or inter session variations in measurements. The GT2FS employed here, on the other hand, contains vertical slices, standing over the FOU, located at specific values of the linguistic variable. This is referred to as Vertical Slice based GT2FS (VGT2FS). VGT2FS has the representational advantages to describe the secondary membership of a primary membership value assigned at a given value of the linguistic variable.

A set of fuzzy production rules are defined to predict the aesthetic assessment of audio-visual stimuli, comprising beautiful facial images of persons, delivering speeches (on human life and relations) with a good tone quality and a soft/pleasing personality. The antecedent of these rules includes test criteria for the occurrence of P200 and N400 signals. There exist several ways to test the occurrence of P200 and N400 signals [15]. One simple approach adopted here checks the occurrence of peak power and total power of the P200 signal between 180 and 220 ms from the onset of the stimulus. Similarly, the appearance of the N400 can be checked by testing the occurrence of the negative peak and average power of the signal between, 380 to 420 ms from the onset of the stimulus [7]. Considering three possible linguistic values of the fuzzy variables, such as High, Low and Medium, and 4 features (concerning peak and total power in the desired bands), we have as many as $3^4 = 81$ rules. Thus the fuzzy rules designed check the test criteria for occurrence of P200 and N400 signals with the motivation of assessing the aesthetic quality of a stimulus into 3 classes: High, Medium and Low. A VGT2FS based reasoning is adopted to infer the degree of membership of the consequent variable, here aesthetic quality of the stimulus. The novelty of the present research lies in a new formulation of VGT2FS reasoning. The new formulation includes i) a method for secondary membership function computation without using any optimization technique, ii) a new method to compute upper and lower firing strength of the classifier rules based on the measure of primary and secondary memberships on the selected measurement points, iii) computing the inference about the degree of aesthetic quality in three classes: High, Medium and Low. After classification of the aesthetic quality in 3 classes, the union of the type-2 inferences is computed for defuzzification and computation of the aesthetic quality in 0 to 100 scales.

Experiments undertaken confirms that the proposed Vertical slice based General Type-2 fuzzy (VGT2Fs) reasoning technique outperform to its competitors by a large margin. Statistical test also confirms the superiority of the proposed technique with its competitors

This paper includes six sections. The second section deals with overall system integration. Section III is concerned with the details of General Type-2 Fuzzy logic based classifier design. Experimental details are presented in section VI. Classifier performance analysis and statistical validation is undertaken in Section V. Conclusions are listed in section VI.

II. SYSTEM OVERVIEW

This section introduces a summarized description of all principles and methodologies adopted to assess the aesthetic qualities of an actor in audio-visual stimuli from the brain response of subjects. Fig. 1 provides a detail description of the overall system. The EEG signals are captured from the scalp of the subjects using $Ag/Agcl_2$ electrodes [16]. The EEG signals are then fed to the exact Low Resolution brain Electromagnetic Topographic Analysis (e-LORETA) software [17], to identify the active brain regions responsible for this work. The active brain lobes detected by e-LORETA are Parietal, Frontal and Temporal lobes. It is known that P200 and the N400 signals have maximum activation in the Parietal and the Fronto-cortex regions respectively, which make sense in the present context. It is interesting to note that P200 has a great role in recognizing visual aesthetic appreciation (beautiful and non-beautiful face images). On the other hand, the N400 signal acquired from Fronto-cortex region (FC_z) and Temporal regions (T_3, T_4 electrodes) assess the degree of aesthetic appraisal for audio signal. So, in the present context

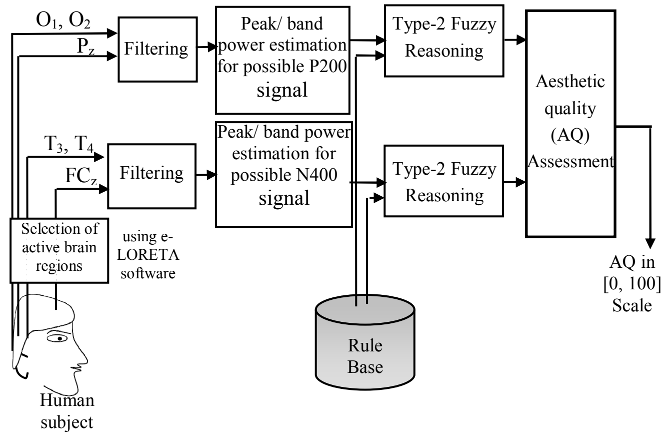

Fig. 1 Block diagram of the complete system for aesthetic quality assessment

we acquire P200 from O_1, O_2, P_z electrodes and N400 from FC_z, T_3, T_4 electrodes.

The raw EEG signals, acquired from the active brain regions are filtered using an elliptical band pass filter of order 10 with the cut off frequency of 2 to 10 Hz [18]. The band pass filter is used to eliminate artifacts and Physiological noise. Then the signals are passed through the Independent Component Analysis (ICA) software [19], to restore 19 independent components from 19 individual channels.

Now, the artifact-free EEG signals are processed to extract the important set of features, which can be easily discriminate the aesthetic qualities of an audio-visual stimulus. In this experiment two sets of EEG features have been utilized, one is P200 features and the other one is N400 features. For P200 features the peak power and total power has been considered between 180 to 220 ms from the onset of the stimulus. Similarly, the occurrence of the negative peak and average power of the N400 signal between 380 to 420 ms from the onset of the stimulus has been considered as the N400 features. Therefore, yielding 4 features × 5 trials/session × 5 session/stimulus = 100 features collected from a single electrode. The resulting features are then fed to the Type-2 fuzzy reasoning module to assess the subjective aesthetic qualities in 0 to 100 scales.

III. GT2FS BASED REASONING FOR AESTHETIC QUALITY ASSESSMENT

A novel General Type-2 Fuzzy Set (GT2FS) based reasoning technique has been presented here.

A. *Construction of Vertical slice based GT2FS (VGT2FS)*

Let, $x_1, x_2, ..., x_n$ be n number of features extracted from the active brain regions of a subject during experiment. A GT2FS is a three tuple $< x, u_{\tilde{A}}(x), \mu(x, u_{\tilde{A}}(x)) >$, where x is the linguistic variable, $u_{\tilde{A}}(x)$ is a primary membership and $\mu(x, u_{\tilde{A}}(x))$ is a secondary Membership. Let, x_i is $\tilde{A}_i$ be a fuzzy proposition used to build up the antecedent part of the fuzzy rule j. Now to construct $\widetilde{A}_i$ both intra-session (Comprising 10 trial in a session) and inter-session (Comprising 7 such session in a week) variations has been considered. The mean (M) and variance (σ) of the intra-session variations are computed which provides one Type-1 Gaussian Membership curve, whose center of the base is located at M and two extremities are located at $M \pm 3\times\sigma$ positions. Thus for d experimental days, d such Gaussian Membership function (MF) have been constructed. Finally, we take maximum and minimum of these Type-1 Gaussian MFs to obtain Upper Membership Function (UMF) and Lower Membership Function (LMF), which in turn produce an Interval Type-2 Fuzzy representation of feature x_i. Next, to satisfy the normality criterion, a flat top approximation has been considered [20]. Now, at the measurement points $x_i = x_i'$, an isosceles triangle with peak =1 is constructed to represent the secondary membership function. This effectively returns a General Type-2 fuzzy set. We replicate this process for all features f_i for i=1 to n.

B. *Secondary membership computation*

The following assumptions are employed to compute secondary memberships.

1. The secondary membership $\mu_{\widetilde{A}_i(x_i')}(u_{mid})$ should have a peak (≈ 1) at the centre of the footprint of uncertainty (FOU) where $u_i = u_{mid} = (\overline{u}_i + \underline{u}_i)/2$, u_i represents the primary membership at a given position $x_i = x_i'$, lying inside the FOU, $\overline{u}_i$ and $\underline{u}_i$ represent the maximum and minimum values of u_i lying on the FOU. This assumption rests on the philosophy that the secondary membership is most certain at the center of the FOU.
2. The secondary membership $\mu_{\widetilde{A}_i(x_i')}(u_i)$ should fall exponentially from the centre of the FOU towards its extremities with a rate of decay controlled by a parameter $\eta > 0$. Formally,

$$\mu_{\widetilde{A}_i(x_i')}(u_i) = \mu_{\widetilde{A}_i(x_i')}(u_{mid}).\exp(-\eta|u_{mid} - u_i|), \quad (1)$$

for $\overline{u}_i \le u_i \le \underline{u}_i$. Tuning of η is performed adaptively using the difference between computed percentage aesthetic quality (PAQ) and self-evaluated oral score in PAQ of the same subject (Fig. 2).

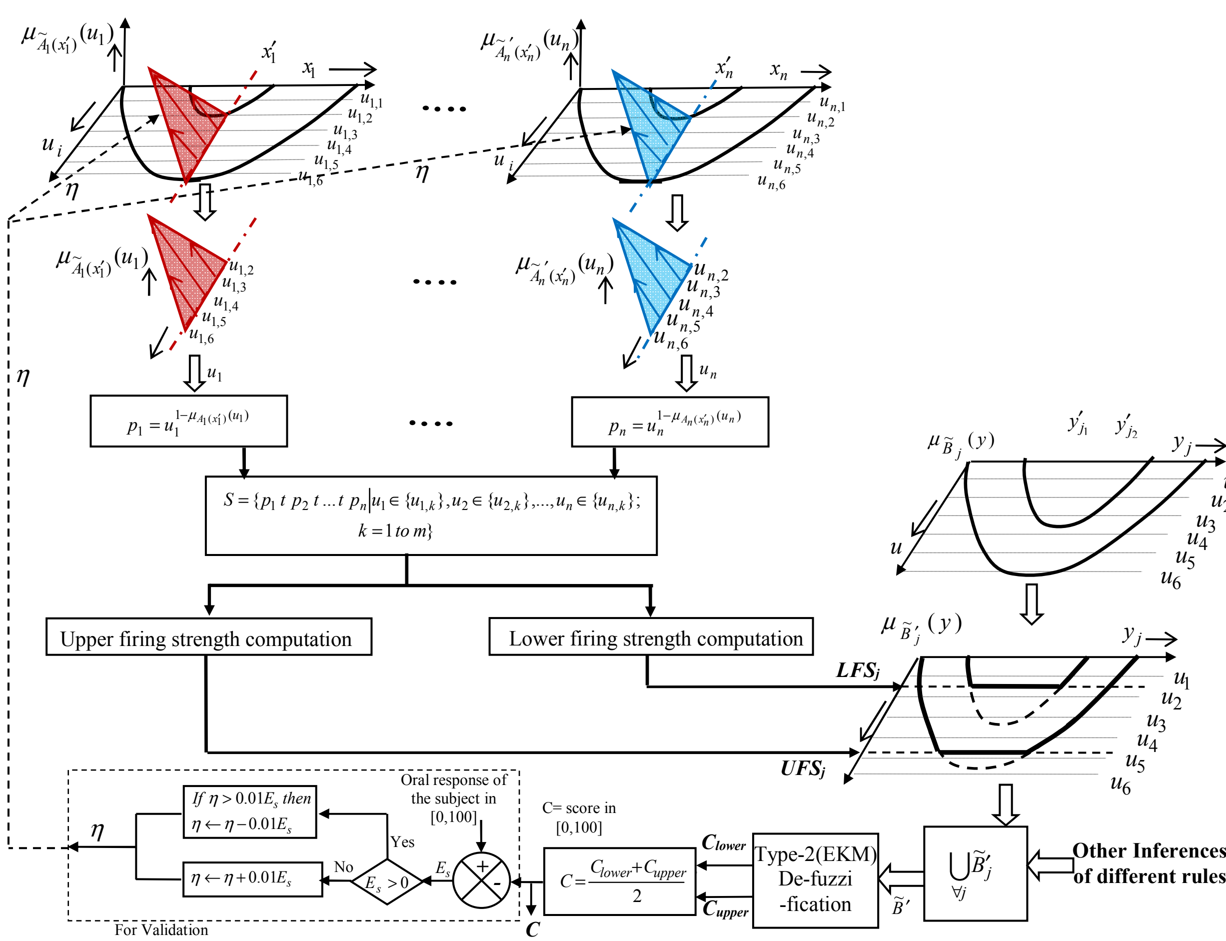

Fig. 2 Architecture of the proposed Vertical slice based General Type-2 Fuzzy Reasoning module

C. Architecture of VGT2FS Based Reasoning

Let us now consider the general type-2 fuzzy rule j is given below:

$$If\ x_1\ is\ \widetilde{A}_{1,j}, x_2\ is\ \widetilde{A}_{2,j}, ..., x_n\ is\ \widetilde{A}_{n,j}, Then\ y\ is\ \widetilde{B}_j.$$

Let, there be n measurement points at $x_i = x_i'$ for i= 1 to n features. The space of the primary membership u_i for the linguistic variable x_i is here partitioned into m discrete values: $u_{i,1}, u_{i,2}, ..., u_{i,m}$. The fuzzy proposition: $x_i\ is\ \widetilde{A}_{i,j}$ here includes a GT2 Membership Function (MF) $\widetilde{A}_{i,j}$. The consequent of the rule: $y\ is\ \widetilde{B}_j$ here includes an interval type-2 fuzzy set $\widetilde{B}_j$, describing the class: High, Medium and Low for the aesthetic quality y (measure of beauty plus tonal quality of a person) present in the stimulus experienced by a subject. The parameter y is defined in the scale [0, 100] and is obtained from the oral response of the subject after examining a given stimulus. To ensure correctness in the assignment of y by the subject, we consider multiple assessment of y by the same subject for the same stimulus. The experiment is conducted on υ days with s sessions in a day comprising tr trials/session. For each day, we construct one Gaussian MF with its mean and variance obtained from the respective mean and variance of one session data of tr trials. Similarly for υ days, we have υ Gaussian MFs. The consequent IT2FS is constructed by taking the maximum and minimum of the above υ Gaussian MFs for all discrete y.

The following steps are adopted for automated reasoning using n antecedent GT2FS MFs and one IT2FS consequent MFs.

1. Use the joint benefit of primary and secondary MFs at $x_i = x_i'$, and $u_i = u_{i,k}$, for k = 1 to m (illustrated in Fig. 2). Here, we modify the primary membership using secondary membership MF value $\mu_{\widetilde{A}_i(x_i')}(u_i)$.

Let the modified primary membership value at (x_i', u_i) be p_i, where,

$$p_i \leftarrow u_i^{1-\mu_{\widetilde{A}_i(x_i')}(u_i)}. \tag{2}$$

It is noteworthy, that the modified primary membership value p_i is more strengthened by powering the original primary membership function (MF) by complement of the secondary MF at the given (x_i', u_i).

2. Next, the t-norm is computed for all $u_i \in \{u_{i,k}\}$. The results are assembled into a set S, defined as

$$S = \{p_1\ t\ p_2\ t \ldots t\ p_n \mid u_1 \in \{u_{1,k}\}, u_2 \in \{u_{2,k}\}, \ldots, u_n \in \{u_{n,k}\}; k = 1\ to\ m\} \tag{3}$$

3. Finally, the Upper Firing Strength (UFS) and Lower Firing Strength (LFS) for rule j have been computed by taking the maximum and minimum of all the modified primary membership values.

$$UFS_j = \{\overline{p_1\ t\ p_2\ t \ldots t\ p_n} \mid \overline{p_1\ t\ p_2\ t \ldots t\ p_n} \geq p_1\ t\ p_2\ t \ldots t\ p_n,\ j \in [1, l]\} \tag{4}$$

$$LFS_j = \{\underline{p_1\ t\ p_2\ t \ldots t\ p_n} \mid \underline{p_1\ t\ p_2\ t \ldots t\ p_n} \leq p_1\ t\ p_2\ t \ldots t\ p_n,\ j \in [1, l]\} \tag{5}$$

where, t is refers to the cumulative t-norms over an argument of n variables and $\underline{p_1\ t\ p_2\ t \ldots t\ p_n} \leq p_1\ t\ p_2\ t \ldots t\ p_n \leq \overline{p_1\ t\ p_2\ t \ldots t\ p_n}$.

Next, the consequent MF of the j-th GT2FS is considered as $\widetilde{B}_j$. The IT2FS inference $[\underline{\mu}_{\widetilde{B}_j'}(y), \overline{\mu}_{\widetilde{B}_j'}(y)]$, is computed by eq. (6) and (7).

$$\overline{\mu}_{\widetilde{B}_j'}(y) = \max(UFS_j, \overline{\mu}_{\widetilde{B}_j}(y)) \tag{6}$$

$$\underline{\mu}_{\widetilde{B}_j'}(y) = \min(LFS_j, \underline{\mu}_{\widetilde{B}_j}(y)) \tag{7}$$

Then for the firing of multiple rules, the overall inference $\widetilde{B}'$ is computed by taking the union of the inferences obtained by using,

$$\widetilde{B}' = \bigcup_{\forall j} \widetilde{B}_j' = \left[\bigcup_{\forall j} \underline{\widetilde{B}'}_j, \bigcup_{\forall j} \overline{\widetilde{B}}_j'\right] \tag{8}$$

Next, the Enhanced Karnik-Mendel (EKM) algorithm has been used to decode (defuzzify) the Type-2 inferences to obtain the lower (C_{l_j}) and upper (C_{r_j}) bound of centroids. Finally, the resulting centroid (C) of IT2MF has been determined by using eq. (9).

$$C = \frac{C_{Lower} + C_{Upper}}{2} \tag{9}$$

Here, the centroid C is represented as the degrees of aesthetic qualities of a given audio-visual stimulus experienced by the subject.

D. Test Session for Aesthetic Quality Assessment

The test session includes 5 sub-sessions in a day, where each sub-session includes 5 trials. Each trial returns one value of aesthetic quality obtained from the oral response of the subject. Thus for 5 trials in a sub-session, we get 5 aesthetic qualities, and take the average of the 5 aesthetic qualities to obtain one average value for each sub-session. Thus, for 5 sub-sessions, we get 5 such average values, one for each sub-session. The mean and variance of these 5 sub-session average aesthetic values are considered as the respective mean and variance of the Gaussian MF.

Let, $Q_{t,j}$ be the user defined aesthetic scores in [0, 100] obtained from the oral response of subject j at the t-th sub-session in a given test session. Let, a be the total number of sub-sessions. Consequently, the Percentage Aesthetic Quality (PAQ_j) of j-th subject, obtained from the oral response, is evaluated by (10).

$$PAQ_j = \frac{\sum_{t=1}^{5} Q_{t,j}}{a} \times 100 \tag{10}$$

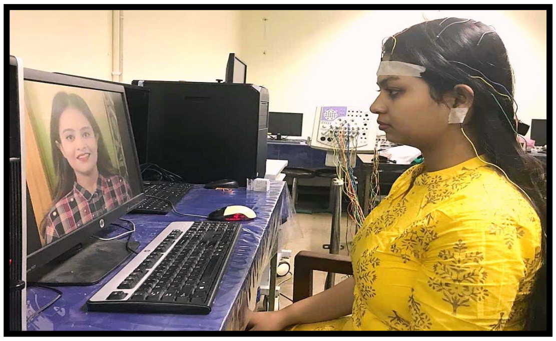

Fig. 3 Experimental Setup for aesthetic quality assessment

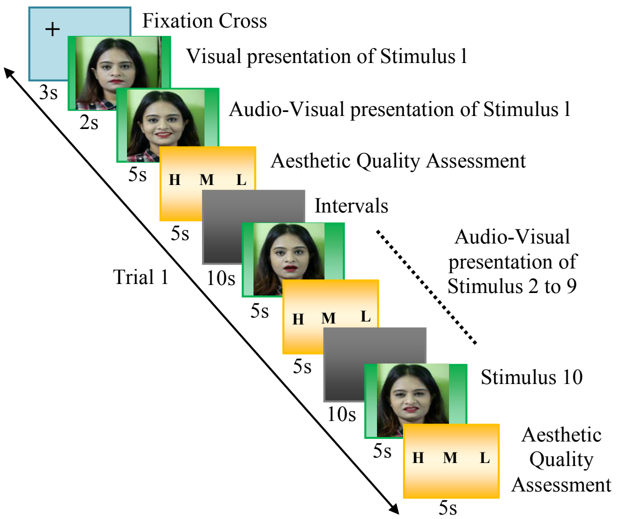

Fig. 4 structure of Stimulus presentation for aesthetic quality assessment

Now, the PAQ of the audio-visual clips is computed by (11).

$$PAQ = \frac{\sum_{j=1}^{R} PAQ_j}{R} \tag{11}$$

where, R is the total number of subjects.

Finally the PAQ is compared with the fuzzy inference C obtained from VGT2FS. So the error metric for stimulus S of all subjects can be evaluated by eq. (12).

$$E_S = \left| PAQ - C \right| \tag{12}$$

This error metric is represented as the relative metric to compare the performance of the proposed reasoning technique with the existing ones.

IV. Experiments And Results

A. The Experimental Framework.

Experiments are undertaken with a standard 21-channel EEG device, manufactured by Nihon Kohden, having a sampling rate of 500 Hz [21]. The aesthetic appreciation of a stimulus experienced by a subject has been captured with the help of Ag/Agcl$_2$ electrodes. According to the 10-20 electrode placement strategy [22], the respective electrodes: Fp$_1$, Fp$_2$, F$_3$, F$_4$, F$_7$, F$_8$, C$_3$, C$_4$, P$_3$, P$_4$, O$_1$, O$_2$, T$_3$, T$_4$, T$_5$, T$_6$, F$_z$, C$_z$ and P$_z$ are placed over the scalp of the subject for EEG recordings.

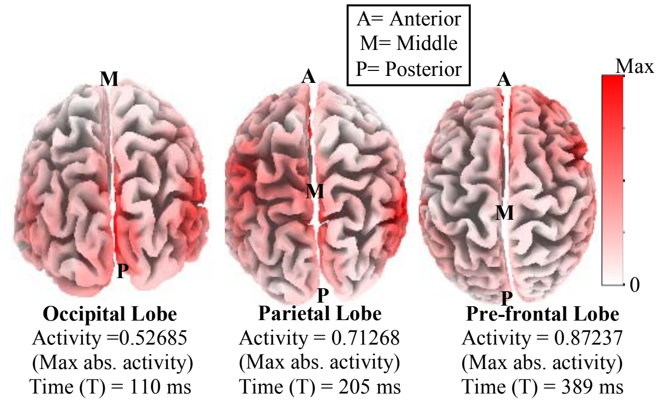

Fig. 5 3D surface plot for aesthetic quality assessment of a audio-visual stimulus

The experiment has been performed on 30 healthy volunteers having normal eyesight in the age group of 20-30 years. Each subject is requested to take a comfortable resting position to avoid any possible contamination of movement related artifacts. The entire experimental framework has been presented in Fig. 3.

B. Stimuli preparation and Presentation

During aesthetic quality assessment, an audio-visual stimulus is presented on the computer screen, comprising beautiful facial images of person (actor) in each trial; delivering speeches with a good tone quality and a soft/pleasing personality. Each audio-visual stimulus is presented to a subject for 5 seconds, as shown in Fig 4. A 10 seconds time gap is maintained between two successive presentations to avoid the residual effect of the previous stimulus. The experiment includes 7 sessions, each session having 10 trials of a person with variation in the audio-visual stimulus. Consequently for 30 subjects, 30 × 10 audio-visual stimuli × 7 session/stimuli × 10 trial/session = 21000 training instances are generated.

C. Experiment 1: Source Localisation using e-LORETA Software.

This experiment aims at determining the active brain regions due to aesthetic appreciation of a subject using exact low resolution brain electromagnetic topographic analysis (e-LORETA) software [23]. The e-LORETA software is a linear inverse solution technique which helps us to evaluate the intra cortical distribution of the EEG signals. As mentioned earlier that the total time duration of the audio-visual stimulus is 5 seconds (5×1000 = 5000 milliseconds) each. In the e-LORETA software, the duration of 5000 milliseconds has been divided into 640 time-frames. Consequently each individual time frame having the length of 7.812 milliseconds.

The most interesting observation that follows from e-LORETA software includes that the occipital region is highly activated for 100-180 ms of durations, representing the visually perceived stimulus. After 180 ms the Parietal region is highly activated when a subject perceives non-beautiful stimulus. Finally, the Frontal lobe and Temporal lobe are highly activated for good tonal quality of a subject. Fig. 5

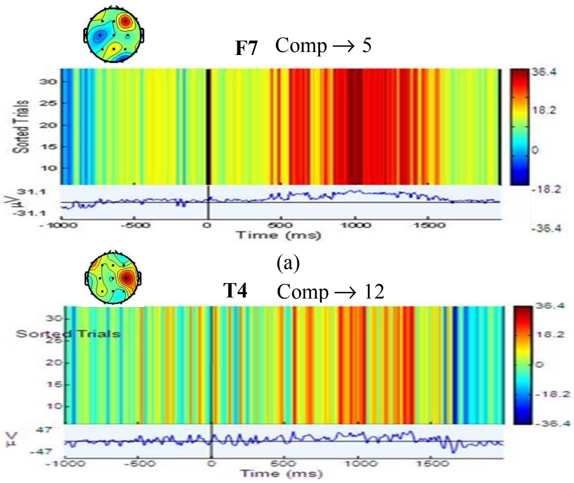

Fig. 6 Artifact free ERP in (a) component 5 and (b) component 12 of ICA

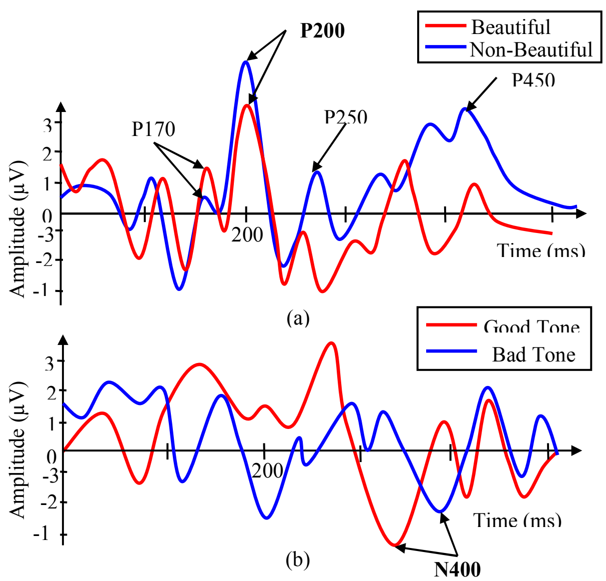

Fig. 7 average ERP signals over 30 participants in response to aesthetic quality assessment of an audio-visual stimulus (a) appearance of P200 signal for non-beautiful stimulus (b) enhance negative amplitude of N400 signals for good tonal quality of the stimulus.

illustrates the e-LORETA solution at 100-180 ms, 180-220 ms and 380-420 ms durations, which signifies the involvement of the above mentioned lobes for the aesthetic quality assessment task of an audio-visual stimulus perceived by a subject.

D. Experiment 2: Filtering and Ellimination of Artifacts

In this experiment, the exact frequency bands are selected by choosing an appropriate filter. To indentify the necessary frequency bands for aesthetic quality assessment, Fourier transform of the EEG signals has been performed. The peaks of the frequency spectrum are lying in 2 to 10 Hz. Thus an elliptical band pass filter with the cutoff frequency of 2 to 10 Hz has been used in this experiment to eliminate the physiological artifacts (like eye blinking, Heart-beat, Blood pressure fluctuations, Mayer-wave etc.) [24]. Here, an elliptic band pass filter of order 10 has been chosen due to its high roll-off and minimal computational over head.

TABLE I
ASSESSMENT OF THE AESTHETIC QUALITY AVERAGED OVER 30 SUBJECTS OF SELECTED AUDIO-VISUAL CLIPS

Subject used to assess the aesthetic quality by the audio-visual clips	List of Audio - visual clips	Percentage Level of Aesthetic Quality (AQ) by a audio-visual clip					
		Visual Aesthetics		Tonal Quality		AQ = (a+c)	Average Score of Aesthetic quality
		Beautiful (a)	Non-Beautiful (b)	Good (c)	Bad (d)		
Subject 1	Clip 1	48	2	33	17	81	88.6
Subject 2	Clip 1	50	0	40	10	90	
…………….	……… …						
Subject 30	Clip 1	46	4	49	1	95	
Subject 1	Clip 2	44	6	23	27	67	60.3
Subject 2	Clip 2	41	9	12	38	63	
……………….	……… …						
Subject 30	Clip 2	40	10	11	39	51	
……………….	……… …						……….
Subject 1	Clip 10	15	35	10	40	25	29.3
Subject 2	Clip 10	20	30	12	38	32	
………….	……… …						
Subject 30	Clip 10	17	33	14	36	31	

Next, the Independent Component Analysis (ICA) [19] has been performed to restore 19 independent components of the brain signals for 19 individual channels of the EEG device. Fig. 6(a) and 6(b) depicts that the component five and twelve are free from artifacts using ICA. Thus these components are fed to the feature extraction module to extract important set of feature for a given subject.

E. Experiment 3: Peak and band power estimation for possible ERP signals

This experiment aims at determining the peak power and total power of possible ERP signals (P200 and N400), associated with the subjective aesthetic quality assessment task. To obtain the possibility of any specific ERP signals, the artifact-free channels are averaged over all possible combination of pleasant/un-pleasant audio-visual stimulus. For possible P200 signal, a positive deflection in the ERP, acquired from the Occipital and the Parietal lobes, is expected within 180-220 ms counted from the onset of a 'non-beautiful' face stimulus. Similarly, for possible N400 signal, enhanced negative amplitude is expected within 380-420 ms from the onset of the stimulus to detect the subject's liking about the tonal quality of the audio-visual signals collected from FCz and T3 electrodes. The appearance of possible ERP signals has been depicted in Fig. 7(a) and Fig. 7(b). It is evident from the figure that the amplitude of the P200 signal is larger for non-beautiful stimulus and the negativity of N400 signal is enhanced for good tonal quality of the stimulus. It needs mentioning that the P200 signal is followed by N400 signal in all cases.

F. Experiment 4:Aesthetic quality Assessment of an Audio-visual stimulus

The prime motivation of this experiment is to identify the top-ranking audiovisual clips depending on their aesthetic qualities. A list of questions (based on geometric feature of face) has been prepared for the subject to determine the

TABLE II
COMPARISON OF E_S OBTAINED BY THE PROPOSED REASONING METHOD AGAINST EXISTING METHODS OF A SUBJECT

Reasoning Techniques	E_S	Run-time in IBM PC Dual-core Machine
Regression using SVM with Gaussian Kernel [29]	4.241	56.28 milliseconds
Regression using SVM with Polynomial Kernel [28]	4.059	57.76 milliseconds
BPNN based Regression [30]	5.136	62.37 milliseconds
Polynomial Regression of order 10	5.736	104.25 milliseconds
Polynomial Regression of order 20	5.269	107.92 milliseconds
Polynomial Regression of order 25	5.029	118.35 milliseconds
Type-I Fuzzy sets [13]	8.349	46.28 milliseconds
IT2FS [25]	3.579	45.71 milliseconds
GT2FS [25]	2.931	95.48 milliseconds
SA-GT2FGG [26]	1.042	96.42 milliseconds
Vertical slice based GT2FS [11]	0.097	94.12 milliseconds
Proposed VGT2Fs model	0.042	**94.78 milliseconds**

aesthetic quality of an audio-visual stimulus, presented on the computer screen. The percentage aesthetic quality assessment of 30 subjects using 10 audio-visual clips are summarized in Table I. Finally, the score of aesthetic quality of each stimulus, averaged over 30 subjects has been presented in the same Table. It is apparent from the Table that the audio-visual clip 1 has the maximum aesthetic quality, whereas, clip 10 has the minimum aesthetic quality.

V. PERFORMANCE ANALYSIS AND STATISTICAL VALIDATION

This section presents the performance analysis of the proposed GT2FS based reasoning technique in aesthetic assessment of the actor in comparison with the existing state-of-the-art techniques, realized for the said application. A two-fold performance analysis is undertaken, where the first fold is concerned with the error metric E_s and run-time complexity as the metrics. In the next fold, the non-parametric Wilcoxon signed rank test is employed to compare the relative merits of the proposed technique in comparison with the existing techniques.

A. Performance Analysis by Error Metric and Run-time Complexity

Table-II provides the summary of the results of the error metric E_S and run-time complexity obtained by the proposed VGTFS based reasoning and traditional type-1 [11],[13], type-2 fuzzy algorithms [25] and non-fuzzy reasoning algorithm, including *L*-th order of polynomial regression [27], support vector machine (SVM) with polynomial kernel [28], SVM with Gaussian kernel [29], Back propagation neural network (BPNN) based regression [30], realized and tested for the present aesthetic quality assessment task. It is apparent from Table II that the proposed reasoning algorithm outperforms its nearest competitors by an error metric of 1.2%. It is also observed from the same table that the run time complexity of the proposed GT2FS algorithm takes 92.7 milliseconds, which is comparably less than the other existing GT2FS based techniques.

TABLE III
STATISTICAL ANALYSIS WITH THE PROPOSED VGT2FS METHOD AS REFERENCE

Existing Reasoning Algorithm with optimal settings of parameters (values not included for space restriction)	Reference Algorithm: Proposed VGT2Fs Algorithm
Regression using SVM with Gaussian Kernel [29]	+
Regression using SVM with SVM-polynomial Kernel [28]	+
BPNN based Regression [30]	+
Polynomial Regression Methods [27]	+
Type-I Fuzzy sets [13]	+
IT2FS [25]	+
GT2FS [25]	+
SA-GT2FGG [26]	+
Vertical slice based GT2FS [11]	+

B. Statistical Analysis using Wicoxon Signed Rank Test

The well-known Wilcoxon Signed rank test [31] has been adopted for statistical validation of the proposed technique. The VGT2FS technique is considered here as the Reference algorithm.

Let. $E_{S,i}^{X}$ be the values of error metric E_S at the i-th training instances of algorithm *X*. Similarly, $E_{S,i}^{Y}$ denotes the value of error metric E_S at the *i*-th training instances of algorithm *Y*. Here, the test statistics is evaluated by

$$W = \sum_{i=1}^{T_r}[\operatorname{sgn}(E_{S,i}^{X} - E_{S,i}^{Y}).r_i] \tag{13}$$

where, T_r denotes the total number of training instances and r_i is the rank of the pair at *i*-th training samples. The null hypothesis H_o indicates the identical performance of a given algorithm with respect to reference algorithm. Table-III provides the results of the statistical test. Here, the plus (minus) sign respectively represent the *W* value of an individual technique is significant (not significant) with respect to the proposed algorithm. It is obtained from the test that the *p*-value is greater than 0.05 at 95% confidence level.

VI. CONCLUSION

The paper introduced a new approach for aesthetic quality assessment of an actor present in audio-visual stimuli by 30 experimental subjects. An ELORETA study with raw EEG acquired from the entire scalp reveals that maximum brain activation during aesthetic assessment takes place from the Parietal, Frontal and Temporal regions. Next the detected EEG signals acquired from the scalp are filtered using Elliptical band-pass filter of 2-10 Hz to eliminate physiological noise. The peak power and total power are extracted from the artifact-free EEG signals of the selected brain lobes (Parietal and Frontal).A VGT2FS based reasoning is undertaken to assess the aesthetic quality of an actor in a given audio-visual stimulus from the peak power and total power of acquired

EEG of the 30 experimental subjects. An error metric is defined to measure the predicted error in aesthetic quality, by taking the difference of VGT2FS response and the subject's oral response, and it is found the VGT2FS based reasoning yields a significant reduction in error in comparison to the same produced by other state-of-the-art techniques. An average score obtained from 30 subjects brain response is used to rank the stimuli based on the descending order of the aesthetic quality. The well-placed stimuli in the rank-list may be recommended for the nourishment of people suffering from psychological disorder and melancholy.

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