A study on the effects of traditional and olfaction enhanced multimedia on pleasantness classification based on brain activity analysis

Aasim Raheel [a], Muhammad Majid [a,*], Syed Muhammad Anwar [b]

[a] Department of Computer Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan
[b] Department of Software Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan

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ABSTRACT

Human emotions are recognized in response to content engaging one (audio music) or two human senses (videos). An enhanced sensation with a more realistic feel could be achievable by engaging more than two human senses. In this study, olfaction enhanced multimedia content is generated by synchronizing traditional multimedia content with an olfaction dispenser for engaging olfactory sense in addition to vision and auditory senses. Brain activity of 20 participants (10 males and 10 females) is recorded with a commercially available EEG headband, while engaging with traditional and olfaction enhanced multimedia content. The human brain activity is used to analyze and differentiate the content engaging two (traditional multimedia content) or more than two (olfaction enhanced multimedia content) human senses. For brain activity analysis, we apply a *t*-test on the power spectra of five frequency sub-bands (delta, theta, alpha, beta, and gamma) of the acquired EEG data in response to traditional and olfaction enhanced multimedia. We observe that alpha, theta, and delta bands are significant in discriminating the response to traditional and olfaction enhanced multimedia content. High brain activity is observed in alpha, theta, and delta bands of frontal channels, while experiencing the olfaction enhanced multimedia content. A user-independent pleasantness classification based on human brain activity is also presented, where classification performance is measured using 10-fold cross validation. We extract features in frequency domain i.e., rational asymmetry (RASM) and differential asymmetry (DASM) from five EEG bands to classify two pleasantness states based on their valence scores using support vector machine (SVM) classifier. Features are further selected based on EEG electrode pair positions and sub-bands. We observed that RASM and DASM features selected from delta band (olfaction enhanced content), and alpha or gamma bands (traditional multimedia content) gives best classification accuracy. We achieved an accuracy of 75%, sensitivity of 77.7%, and specificity of 72.7% in response to olfaction enhanced multimedia content and an accuracy of 68.7%, sensitivity of 71.4%, and specificity of 69.2% in response to traditional multimedia content in classifying pleasant and unpleasant states using SVM. We observed that classification of pleasant state was comparatively better with olfaction enhanced multimedia content than traditional multimedia content.

1. Introduction

Emotions play a vital role in evaluating an observer's experience with digital content in terms of viewing, selection, and immersion. This content could engage single- or multiple-human senses [1]. Traditionally, emotions were recognized by using facial expressions [2] and speech signals [3]. These methods had limitations and dependency on social and cultural environment of the subjects [4]. These limitations could be overcome by using functional neuro-imaging techniques such as electroencephalography (EEG), positron emission tomography (PET),

and functional magnetic resonance imaging (fMRI). Among these, EEG have gained significant attention because of the ability to perform a more objective evaluation of the signals and the ease in mobility while acquiring data [5].

Emotions are representative of complex cognitive functions that involve different regions of the brain and are associated with different neural oscillations [6]. Human brain is divided into four lobes i.e., frontal, temporal, parietal, and occipital [7] and is shown in Fig. 1. The frontal lobe is responsible for cognitive functions and muscular movements. The parietal lobe processes functions relevant to gustatory and

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tactile senses. The occipital lobe processes the sense of vision, whereas the temporal lobe processes auditory and olfactory senses. Emotion annotation is performed based on valence and arousal scores [8]. The valence-arousal scale used for emotion annotation is shown in Fig. 2. Valence represents pleasant/unpleasant state, while arousal represents calm/excited state of an individual.

Emotion recognition using EEG signals require multiple electrodes placed at selective locations on the head scalp. EEG signals provide good time resolution, which helps to analyze brain activity in response to an external stimuli. Emotion related activity normally occurs at the frontal region of the brain [9,10]. Power spectra of the EEG signal from each electrode is characterized in distinct frequency bands ranging from $1-100$ Hertz (Hz): $1 <$ delta < 4 Hz, $4 <$ theta < 7 Hz, $8 <$ alpha < 13 Hz, $13 \square$ beta < 30 Hz, and gamma > 30 Hz [11]. Alpha-power asymmetry derived from spectral differences of symmetric electrode pairs placed on the human scalp is one of the indicators of emotional states [12–14]. The power change in alpha and theta bands of the right parietal lobe of the brain is associated with human emotions [14–16]. Spectral changes and brain region activation (such as power asymmetry in the beta band on parietal region) are associated with human emotions [17]. Similarly, spectral differences at right parietal part of the brain in the gamma band also contributes in emotion recognition using EEG [18]. The aforementioned methods provide evidence for using EEG signals to analyze brain activity and identify different emotional states.

Traditionally, video content makes use of two synchronized components (audio and video) and hence involve two human senses (auditory and vision). This setup is also known as bi-sensorial media. The actual human experience with the environment indulges five human senses: visual (sight), auditory (hearing), tactile/haptic (touch), olfactory (smell), and gustatory (taste). The experience with multimedia content can be enriched by involving the sense of smell, touch, and taste in addition to sight and hearing in traditional videos. Such content was referred to as multiple-sensorial media (Mulsemedia) [19]. Mulsemedia content is generated by artificially generating fragrances, air or humidity effects with audio-visual content to engage multiple human senses. It makes the audio-visual content look real and is generated by identifying time stamps in a video clip. Further, synchronization is performed with devices like scent dispenser, haptic vest, air, and motion effects [20,21].

1.1. Related work

Brain activity was analyzed in response to stimuli engaging only one human sense like auditory [22,23], vision [24], olfaction [25,26], and tactile [27]. In Ref. [22], emotion analysis and brain response to audio music (engaging sense of hearing) for different age groups was presented. The impact of different music genres on human emotion was also investigated. In Ref. [23], emotional responses were evaluated in response to music by using EEG signals. For classification, energy in different bands was used as features. In Ref. [24], human brain activity was analyzed in response to images that engaged the sense of vision. Images were presented as a stimuli and statistical tests were applied on
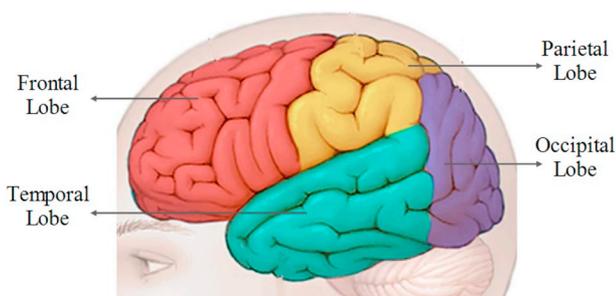

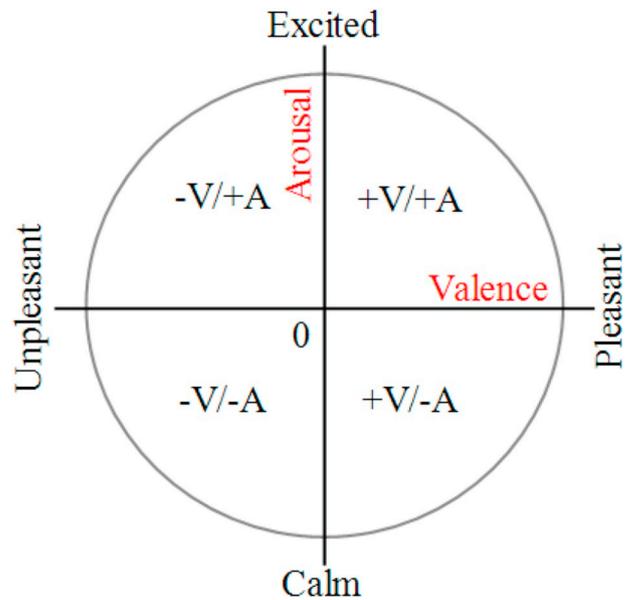**Fig. 1.** Human brain anatomy subdivided into four different lobes.

Fig. 2. Valence-arousal plane for emotion annotation.

different bands to evaluate these nightscape images using EEG signals. In Ref. [27], brain activity was analyzed in response to pleasant and unpleasant touch by only engaging the sense of tactile. Physiological correlates of affective tactile sense were observed in different bands, while caressing of the human forearm with textile fabric resulting in pleasant and unpleasant feelings. In Ref. [25], human emotions were classified into pleasant and unpleasant odors using power spectral densities as features from different bands of EEG signals by only engaging the olfactory sense. In Ref. [26], EEG signals were used to classify pleasant and unpleasant odors. Discrete wavelet transform and statistical measures were used as features. It was observed that the frontal and central lobes are discriminating for odor pleasantness classification.

Emotion recognition and brain activity analysis has been performed in response to videos engaging two human senses (vision and auditory). In Ref. [1], emotions were classified into three valence and arousal classes in response to video clips. Beta and gamma bands of the temporal electrodes were considered as more significant for classifying pleasantness states in response to videos. In Ref. [28], database for emotion analysis using physiological signals (DEAP) was used for emotion classification by utilizing the minimum number of electrodes and frequency bands of EEG signals. For emotion classification, wavelet domain features were extracted from the acquired EEG signal and the high frequency bands (gamma) yielded higher accuracy as compared to low frequency bands. In Ref. [29], movie clips were used to induce emotions, which were classified in the valence and arousal plane. Short-time Fourier transform was used to extract features along with various frequency sub-bands. The gamma band in temporal lobe, and delta and beta bands in parietal and frontal lobes were found to be more sensitive for the emotion recognition task. In Ref. [30], emotion recognition in response to videos was proposed using deep learning. Two different datasets i.e., DEAP and SJTU emotion EEG dataset (SEED) were used to classify valence, arousal, and dominance classes using EEG data.

Human emotions and brain activity analysis in response to mulsemedia (simultaneously engaging more than two human senses) has not been investigated in detail. In Ref. [31], tactile enhanced multimedia was generated by synchronizing a fan and heater with traditional multimedia to simultaneously engage three (vision, auditory, and tactile) human senses. It was shown that by engaging an additional sense within traditional multimedia, significantly evokes different emotions. The emotion classification accuracy in response to tactile enhanced

multimedia was improved by using frequency domain features [32]. Olfaction enhanced content was generated by identifying and synchronizing selected parts in the multimedia content with olfaction dispenser to engage the sense of smell, vision, and hearing [34]. A user smells an odor when the multimedia content involves a scene with fragrance, giving a real-life feel. In Ref. [33], an olfaction enhanced game was used to deliver immersive gaming experience to the users. Emotional responses i.e., fear and curiosity were measured and analyzed using subjective questionnaires. An enhancement in user experience was reported by utilizing olfactory information with the game. A brief summary of the emotion recognition studies in response to different stimuli is presented in Table 1.

The synchronization and like/dislike factors for olfaction enhanced content have been studied in subjective manner. Similarly, emotion recognition in response to audio, video, and tactile enhanced multimedia using EEG has been studied. Emotion analysis in response to different odors by engaging only the sense of smell using EEG has been studied. The impact of olfaction enhanced multimedia on human brain activity and emotions is yet to be explored. To the best of our knowledge this is for the first time, we recorded the human brain activity using EEG headband, while viewing olfaction enhanced multimedia content. The main objective of this work is to differentiate the traditional and olfaction enhanced multimedia content in terms of human's brain activity. The impact of olfaction enhanced multimedia on pleasantness recognition using brain activity is also explored in this study.

1.2. Our contributions

Our aim in this study is to analyze brain activity in response to olfaction enhanced multimedia content. To this end, we highlight the importance of different frequency bands by applying a statistical approach (*t*-test) and analyze each band of each electrode in our experiments. We classify valence states (pleasant and unpleasant) using EEG signals recorded by engaging participants in traditional and olfaction enhanced multimedia content. A wearable headset was selected for this purpose with frontal and temporal electrodes. Two groups of frequency domain features were extracted from the acquired data and labeled based on the self assessment manikin (SAM) scores. Support vector machine (SVM) was used to classify pleasant and unpleasant states. We analyzed the significance of frontal and temporal electrodes and the impact of EEG bands in recognizing pleasantness states. Our main contributions are.

1. Olfaction enhanced multimedia content is generated for engaging three human senses by synchronizing olfaction dispenser with the traditional multimedia content.
2. Brain activity is analyzed using signals recorded from commercially available MUSE EEG headband for statistical significance of different bands in response to traditional and olfaction enhanced multimedia content.

3. Our innovative experimental setup has shown that olfaction enhanced multimedia content is better suited for pleasantness classification.

The remainder of the paper is organized as follows. Our proposed methodology for brain activity analysis and pleasantness classification in response to traditional and olfaction enhanced multimedia using EEG signals is discussed in Section 2. Experimental results based on statistical significance and pleasantness classification are presented in Section 3. Discussion of our results is presented in Section 4 followed by conclusions in Section 5.

2. Materials and methods

Our proposed methodology, shown in Fig. 3, classifies pleasantness states and analyze brain activity in response to traditional and olfaction enhanced multimedia. The olfaction enhanced multimedia content was generated by synchronizing video clip with an olfaction dispenser. EEG data of subjects were acquired in response to both the traditional and olfaction enhanced multimedia content, which were pre-processed to obtain EEG bands for brain activity analysis and classification. For brain activity analysis, EEG frequency bands data were grouped into traditional and olfaction enhanced multimedia content groups. A statistical *t*-test was employed to determine the significant EEG bands between traditional and olfaction enhanced multimedia content. For pleasantness classification, two groups of frequency domain features were extracted from the EEG bands. The performance was evaluated for each feature type, electrodes pair, and EEG bands for two states (pleasant and unpleasant) classification using SVM classifier. The details of each block (Fig. 3) are described in the following subsections.

2.1. Content generation

The experimental setup (Fig. 4) consisted of a display screen and a micro-controller based electronic device (olfaction dispenser) capable of dispensing the scent placed in the dispenser. Olfaction enhanced multimedia was generated by synchronizing traditional multimedia with olfaction dispenser by identifying time-stamps. These indicated the scenes within the multimedia content where the sense of smell (in addition to auditory and vision) was used. Olfaction dispenser was placed at a height of 0.4 m. Subjective tests showed that it took approximately 2.5–3 s to smell a scent dispensed by the dispenser at this height. Hence, the scent was dispensed 2.75 s before the scene (with fragrance content) started in each trial. The participants were seated in a comfortable chair while viewing the content displayed on an LED screen of 55 inches placed at a distance of 2 m from viewing point.

We selected a video clip (duration- 45 s) from the movie 'Tangled', where the character moves (after 5 s from the start) towards a bucket of flowers and smells (7th second) the fragrance. These time-stamps are identified and synchronized with the olfaction dispenser, which

Table 1

Summary of emotion recognition and analysis studies in response to different stimuli.

| Ref.	Stimulus	Senses Engaged	Sensors Used	Emotions Classified
[1]	Video Clips	Vision, Auditory	EEG, Eye Tracking	Pleasant, Unpleasant, Neutral, Calm, Medium, Activated
[22]	Music	Auditory	EEG	Happy, Sad, Love, Anger
[23]	Music	Auditory	EEG	High/Low Valence, Arousal
[24]	Images	Vision	EEG	Fear
[25]	Odors	Olfaction	EEG, ECG	Pleasant, Neutral, Unpleasant
[26]	Odors	Olfaction	EEG	Pleasant, Unpleasant
[27]	Textile Fabrics	Tactile	EEG	Pleasant, Unpleasant
[28]	Musical Videos	Vision, Auditory	EEG	High/low Valence, Arousal
[29]	Video Clips	Vision, Auditory	EEG	Joy, Amusement, Tenderness, Anger, Disgust, Fear, Sadness
[30]	Video Clips	Vision, Auditory	EEG	Valence, Arousal, Dominance
[31,32]	Tactile Enhanced Clips	Vision, Auditory, Tactile	EEG	Happy, Angry, Sad, Relaxed
[33]	Olfaction Enhanced Game	Vision, Auditory, Olfaction	Subjective Analysis	Fear, Curiosity
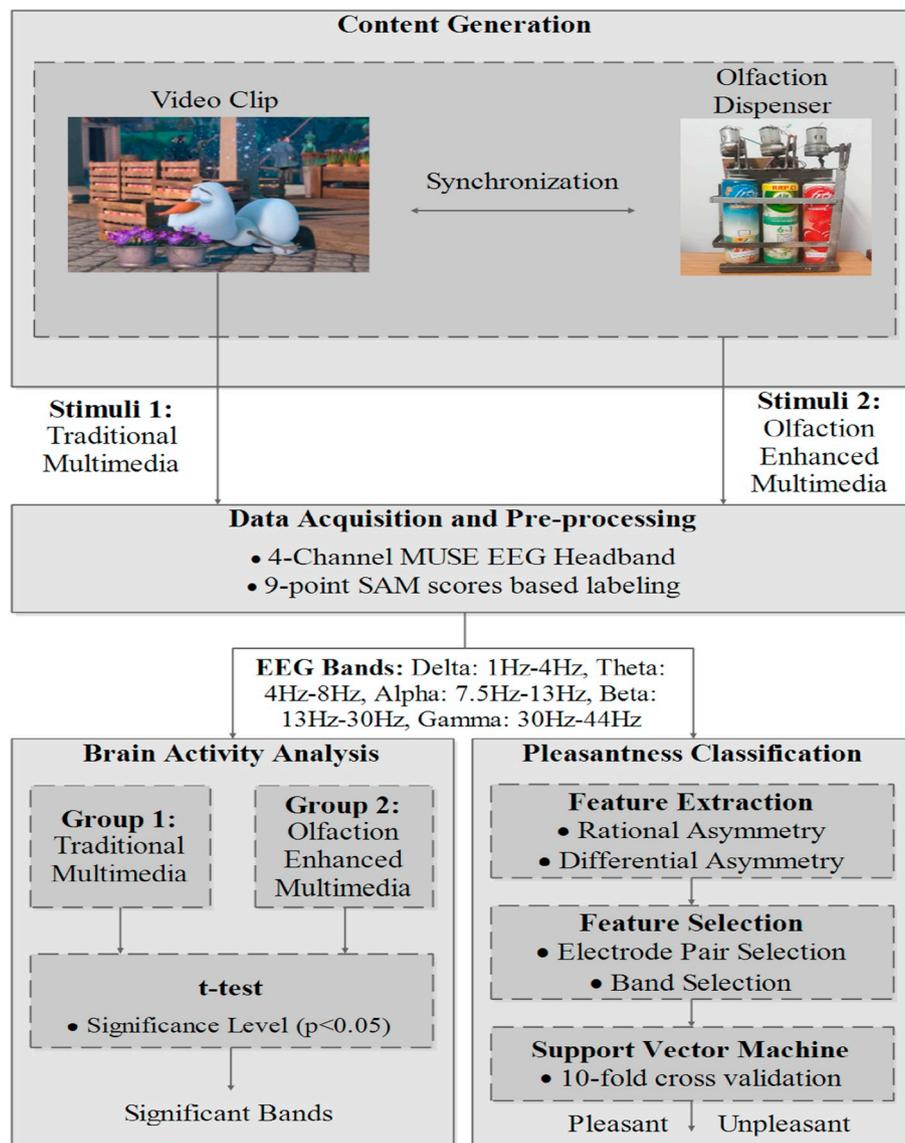
Fig. 3. Proposed methodology for brain activity analysis and pleasantness classification in response to olfaction enhanced multimedia using EEG signals.
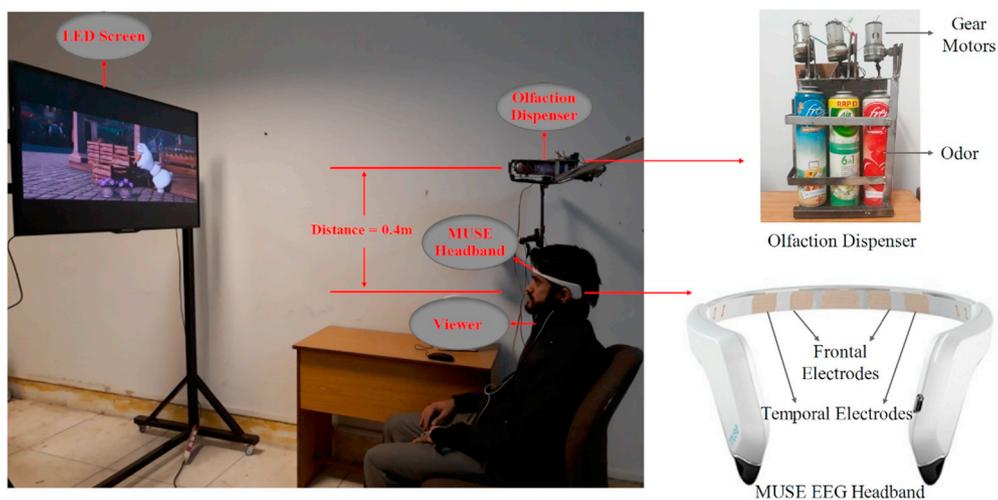

Fig. 4. Experimental setup for data acquisition in response to olfaction enhanced multimedia.

dispenses the scent at an appropriate time. Different viewer's rated the synchronization of dispenser with like/dislike scores. The best frame (for synchronization) was identified by user's (not involved in the EEG based study) evaluation/feedback of the setup. The start-, end-, and synchronization-frames (with time-stamps) in the movie clip for the olfaction dispenser and signal analysis are shown in Fig. 5.

2.2. Data acquisition and pre-processing

A total of 20 participants (10 males and 10 females) were involved in this study having age between 18 and 25 years (median- 21). The participants reported no mental illness, inability to smell, hearing, or viewing problems. Brain signals were recorded at a sampling rate of 256 Hz using MUSE EEG headband having 4 channels (*AF*7, *AF*8, *TP*9, *TP*10) and a reference electrode. MUSE is commercially available and easy to use EEG headband and has been successfully used for stress and emotion classification problems [31,35]. The electrode positioning in MUSE headband follows the international 10–20 system (Fig. 6). Frontal- and temporal-electrodes are made up of conductive material (silver) and silicon rubber respectively.

The experimental procedure for data acquisition (Fig. 7) included an initial introduction to the scope of the experiment. This was followed by EEG data acquisition while showing the multimedia clip (from Tangled movie) without olfaction effect and user rating on a 9-point SAM scale. The same clip with olfaction enhancement was then displayed to the user and EEG data was recorded. Finally, the user rated this enhanced experience on a 9-point SAM scale. The whole procedure took 10.5 min (average) for each participant.

The acquired data was pre-processed for noise removal before further processing. The centrally positioned electrode on the MUSE headset was used for active noise suppression. For minimal ocular and muscular noise in the recorded EEG signals, participants were instructed to minimize eye blinks and unnecessary movements. Five frequency bands (delta: 1*Hz*-4*Hz*, theta: 4*Hz*-8*Hz*, alpha: 7.5*Hz*-13*Hz*, beta: 13*Hz*-30*Hz* and gamma: 30*Hz*-44*Hz*) were extracted from each channel of the recorded EEG signals.

2.3. Brain activity analysis

A *t*-test is used to determine significant difference between the means of two groups. In order to find the significant EEG bands from the data acquired in response to traditional and olfaction enhanced multimedia, a *t*-test was applied on the power spectral densities of each EEG band. The test decision was based on the value of null hypothesis (h) and p-value (p). The difference between the groups are statistically significant if $p < 0.05$ and $h = 1$.
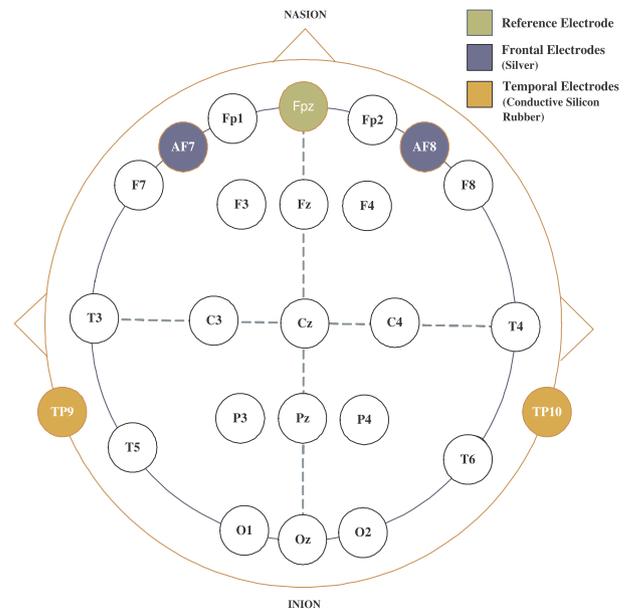

Fig. 6. Electrode positioning of MUSE EEG headband according to international 10–20 system.

2.4. Pleasantness classification

The pre-processed EEG data was used to classify the pleasantness states in response to traditional and olfaction enhanced multimedia. For this purpose, features were extracted from each EEG band and feature selection was performed based on electrode pair and EEG band selection. The selected features were used to classify the pleasant and unpleasant state using SVM classifier. The details of each sub-blocks are as follows.

2.4.1. Feature extraction

The asymmetrical frontal spectral powers and differences in EEG are reflected as change in the valence score and were found to be correlated with emotions [36,37]. Therefore two groups of values: (i) rational asymmetry (RASM) and (ii) differential asymmetry (DASM) were extracted from each frequency sub-band (delta, theta, alpha, beta, and gamma) of signals from each EEG electrode pair ((*AF*7, *AF*8) and (*TP*9, *TP*10)) and used as features.

RASM and DASM are the ratio and difference of spectral powers on symmetrical electrode pairs. These pairs are identified as electrodes which are placed at same position and distance from a center point on the right- and left-hemisphere of the brain. RASM and DASM were calculated for each band of channel pair as follows,
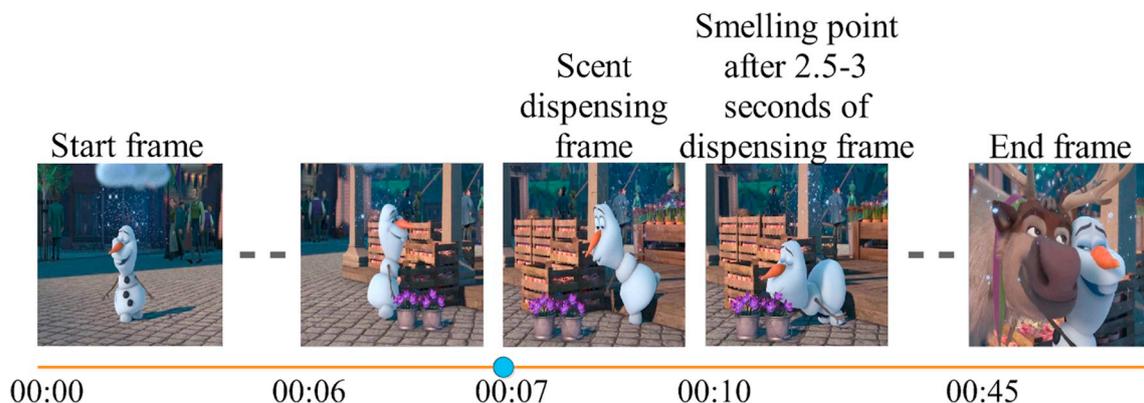

Fig. 5. Screen grab from the movie *'Tangled'* showing start-, end-, and synchronization-frame with olfaction dispenser.
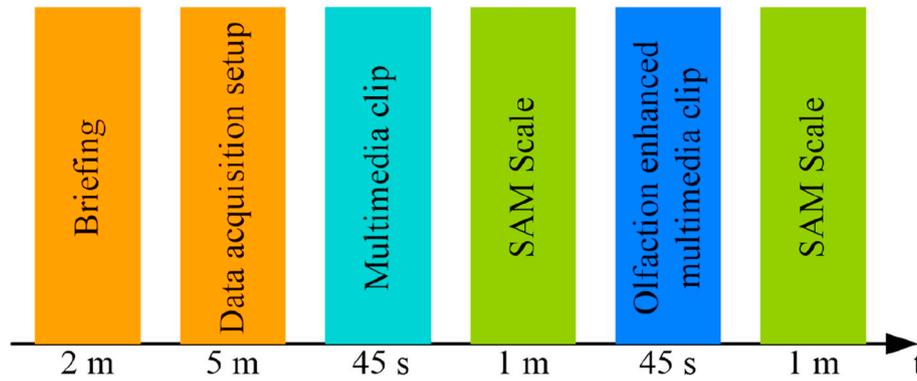
Fig. 7. Experimental procedure followed in this study for data acquisition against traditional and olfaction enhanced multimedia.

$$RASM_B = \frac{P_R}{P_L}, \qquad (1)$$

$$DASM_B = P_R - P_L, \qquad (2)$$

where P_R and P_L are the spectral powers at electrodes on the right and left hemispheres respectively, and B represents the frequency bands. The power spectral density is calculated as,

$$PSD = \sum_{n=-\infty}^{\infty} |c_n|^2 \delta(f - nf_o), \qquad (3)$$

where $|c_n|$ is the Fourier series coefficient and $\delta(f - f_o)$ represents the shifted impulse function.

2.4.2. Feature selection

We extracted 10 features each of RASM and DASM from every electrode pair of each frequency band. Feature selection was implemented to reduce the feature vector length by removing redundant values. Discriminating features for pleasantness classification in response to traditional and olfaction enhanced multimedia were identified by selecting features from different electrode pairs and EEG frequency bands. For electrode pair based feature selection, RASM and DASM features from frontal and temporal electrode pairs were used for pleasantness classification. For EEG bands based feature selection, RASM and DASM features from each individual band and combination of different EEG bands from selected electrode pair were used for pleasantness classification.

2.4.3. Support vector machine

SVM was used for the classification (2 valence states) in response to traditional and olfaction enhanced multimedia. As the proposed scheme is user independent, therefore we used 10-fold cross validation for testing the classifier performance. In 10-fold cross validation, data is divided into 10 equal parts and each part is once used for testing and remaining nine parts are used for training. SVM has been widely used for emotion recognition using EEG signals [38]. An SVM classifies data based on labeled training samples by introducing hyper-planes. A hyper-plane or decision plane is capable of separating a set of objects associated with different classes using support vectors. The distance between the separating hyper-plane and the closest training point is considered as margin.

3. Experimental results

For a better understanding of the association between the brain activity and pleasantness states in response to traditional and olfaction enhanced multimedia, we divided our experiments into two parts. We looked at the statistical significance of different EEG frequency bands and performed brain activity analysis, and also performed pleasantness

classification. The experimental results are discussed in the following subsections.

3.1. Statistical significance of different EEG bands and brain activity analysis

To understand the role of various EEG bands in response to traditional and olfaction enhanced multimedia, we applied a two sample t-test on the spectral power of each band of each electrode. Significance of bands against these two stimuli was found by dividing the acquired data into two separate groups: EEG data recordings while displaying the (i) traditional multimedia and (ii) the olfaction enhanced multimedia. EEG bands having p-values lesser than 0.05 were identified as significant. The results of t-test for traditional- and olfaction enhanced-multimedia in terms of p-values against each band of each electrode are shown in Table 2. We observed that alpha band was more significant on TP10 channel. Whereas delta, theta, and alpha bands on AF8, were found significant (p-value less than 0.05) for discriminating between traditional and olfaction enhanced multimedia content. Box plots for the spectral power of each band on channels AF7, AF8, TP9, and TP10 for traditional and olfaction enhanced multimedia are shown in Fig. 8. These box plots show a significant difference among the spectral powers and the results are consistent with those of t-test. Moreover, among the available electrodes, AF8 channel (with statistically significant alpha, theta, and delta bands) was found to be discriminative in pleasantness classification while engaging the sense of smell (with vision and hearing) in multimedia.

We analyzed the brain activity in response to traditional and olfaction enhanced multimedia using power spectral density. Brain maps of all bands (delta, theta, alpha, beta, and gamma) on all channels are shown in Fig. 9. The high and low activity in the brain maps is represented with red and yellow colors respectively. We observed that delta, theta, and alpha bands have higher brain activity in response to olfaction enhanced multimedia as compared to traditional multimedia on AF8 channel. Similarly, alpha band was more activated in response to traditional multimedia on TP10 channel as compared to the olfaction enhanced multimedia. An example of EEG spectral power of four

Table 2
P-values against traditional and olfaction enhanced multimedia on all bands of each EEG channel.

Channel	EEG band				
	Delta	Theta	Alpha	Beta	Gamma
TP9	0.37	0.47	0.25	0.26	0.10
TP10	0.17	0.08	**0.04**	0.33	0.20
AF7	0.23	0.20	0.19	0.12	0.12
AF8	**0.02**	**0.02**	**0.04**	0.09	0.18

The bold values in Table 2 represent EEG bands, which are significantly different against traditional and olfaction enhanced multimedia.
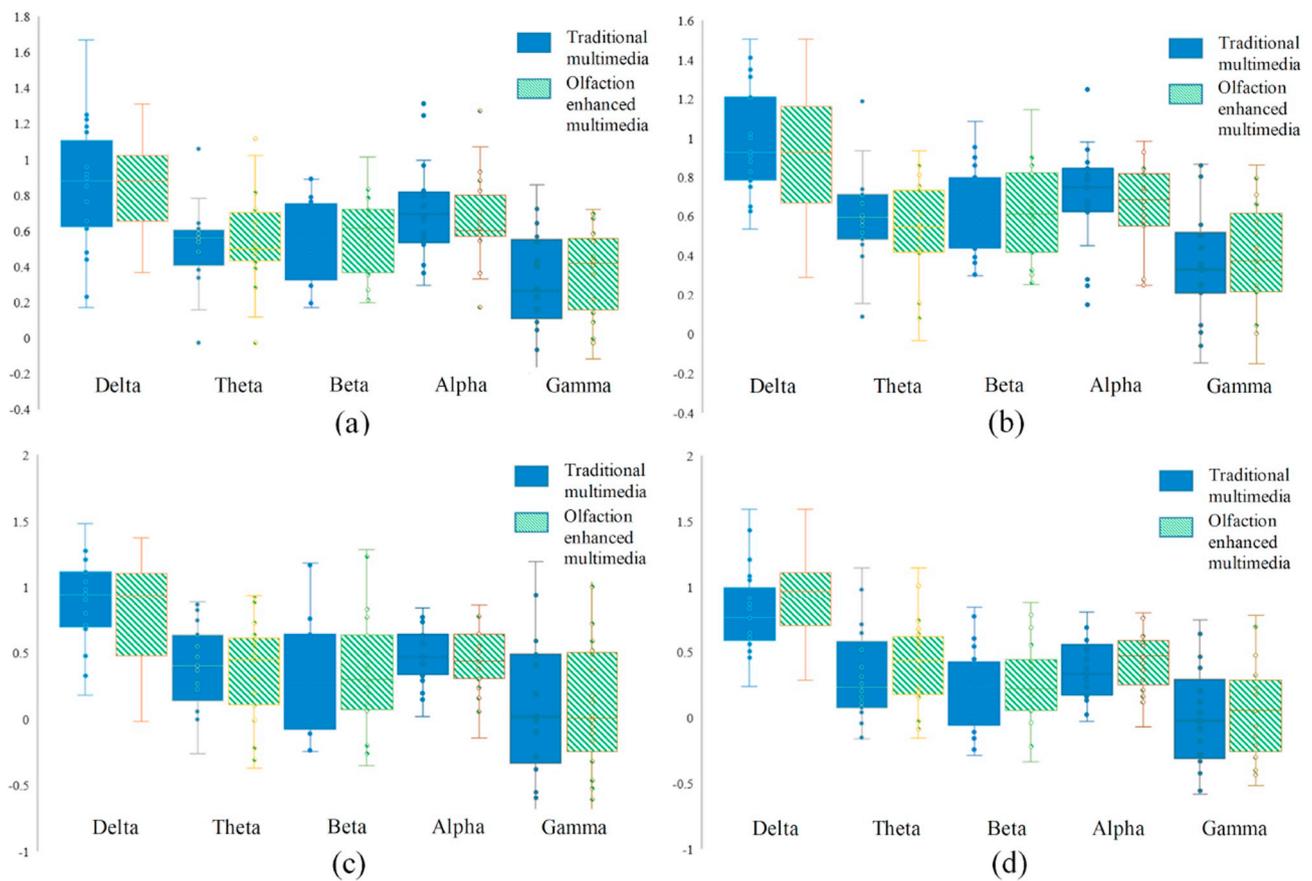
Fig. 8. Box plot of different EEG bands against traditional and olfaction enhanced multimedia for EEG channels (a) *TP*9 (b) *TP*10 (c) *AF*7 (d) *AF*8.
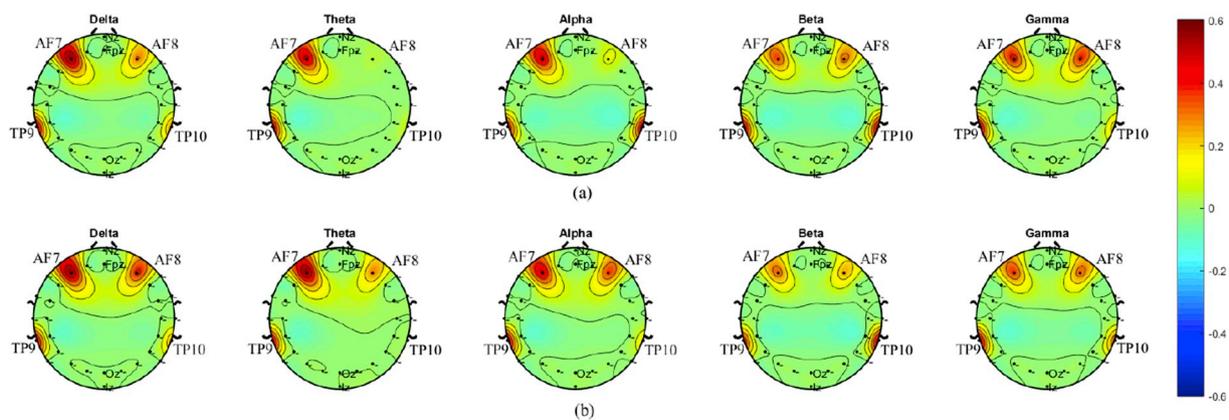

Fig. 9. Brain map of delta, theta, alpha, beta, and gamma bands of (a) traditional multimedia (b) olfaction enhanced multimedia.

channels for five EEG bands in response to traditional and olfaction enhanced multimedia is shown in Fig. 10 and Fig. 11 respectively.

3.2. Pleasantness classification analysis

The acquired EEG data was labeled by using the SAM questionnaire (9-point scale). Pleasantness was divided into pleasant and unpleasant states based on the mean value of the valence scores of the users. The mean and standard deviation of valence scores in response to traditional multimedia are 6.57 and 1.80 respectively. Similarly, the mean and standard deviation of valence scores in response to olfaction enhanced multimedia are 6.57 and 2.02 respectively.

An SVM based classification algorithm was applied to classify these states (pleasant and unpleasant) in response to traditional and olfaction enhanced multimedia. A 10-fold cross validation was used by dividing the data into 10 equal parts. Each of these parts was once used for testing and remaining parts were used for training. We used the sequential minimal optimization algorithm with polynomial kernel. The complexity parameter is set to default value of 1. The classifier performance was evaluated in terms of accuracy, root absolute error (RAE), root relative squared error (RRSE), mean absolute error (MAE), root mean squared error (RMSE), and kappa statistics.

Table 3 shows the classification accuracy, MAE, RMSE, RAE, RRSE, and kappa statistic using SVM for traditional and olfaction enhanced multimedia. RASM and DASM features were extracted from five EEG bands from four channels (two electrode pairs) resulting in a total of 20
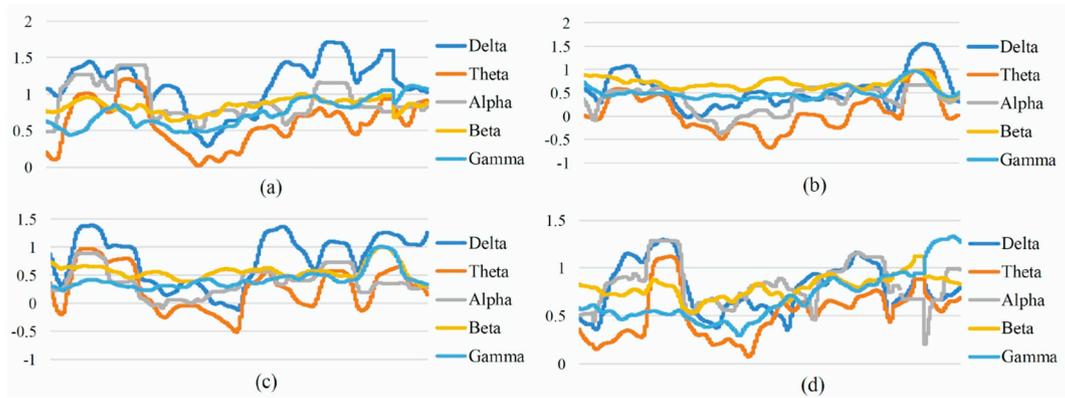
Fig. 10. Example of spectral power of EEG bands data against traditional multimedia for channels (a) *TP*9 (b) *AF*7 (c) *AF*8 (d) *TP*10.
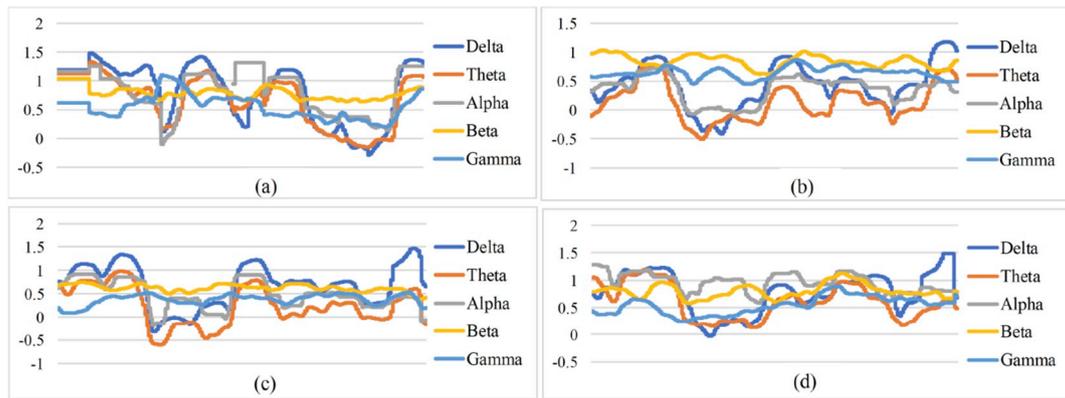

Fig. 11. Example of spectral power of EEG bands data against olfaction enhanced multimedia for channels (a) *TP*9 (b) *AF*7 (c) *AF*8 (d) *TP*10.

Table 3
The performance of the proposed pleasantness classification method using EEG in response to traditional and olfaction enhanced multimedia.

Stimuli	Accuracy	MAE	RMSE	RAE	RRSE	Kappa
Multimedia	60%	0.4	0.632	80	125.92	0.139
Olfaction Enhanced Multimedia	60%	0.4	0.632	80	126.49	0.2

Fig. 12. Precision, recall, and F-measure for traditional and olfaction enhanced multimedia.

feature values. We classified two valence states (pleasant and unpleasant) with an accuracy of 60% against both olfaction enhanced and traditional multimedia. The same value of MAE, RMSE, and RAE was observed in response to both the traditional and olfaction enhanced multimedia. Whereas a large value of RRSE was observed in case of olfaction enhanced multimedia content, when compared with traditional multimedia content. We observed a higher value of kappa for olfaction enhanced multimedia which suggests a higher level of agreement between the training and testing data. From the precision, recall, and F-measure values (Fig. 12) we observe that olfaction enhanced multimedia gives a higher value for F-measure as compared to traditional multimedia.

3.2.1. Classifier performance by selecting features from electrode pairs

The performance of our proposed pleasantness classification method was evaluated by selecting RASM and DASM features from frontal and temporal electrode pairs for two classes of valence classification against traditional and olfaction enhanced multimedia content. The feature vector length was reduced to half (10 features) by selecting RASM and DASM features from each electrode pair. Table 4 shows the classifier performance by selecting RASM and DASM features from each frontal
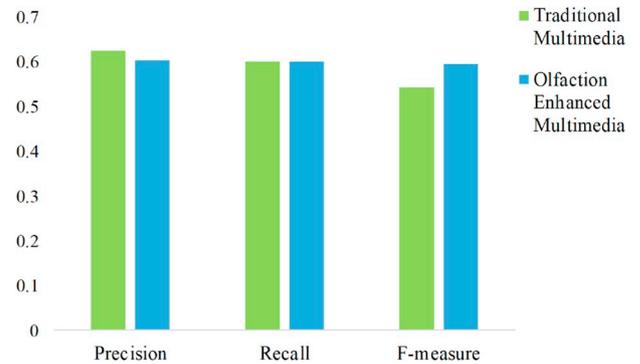
and temporal electrode pair *i.e.,* (*AF*7, *AF*8) and (*TP*9, *TP*10). It is evident that features from frontal pair achieve high accuracy (65%) as compared to temporal pair in recognizing pleasantness states in response to traditional multimedia. Moreover, we observed high kappa value and low MAE, RMSE, RAE, and RRSE in case of features selected from frontal pair as compared to temporal pair for traditional multimedia. Whereas, RASM and DASM features from temporal electrode pair achieved the highest accuracy of 70% against olfaction enhanced multimedia as compared to features from frontal electrodes. Moreover, we observed high kappa value and low MAE, RMSE, RAE, and RRSE values in case of features selected from temporal pair as compared to frontal pair for olfaction enhanced multimedia content.

Precision, recall, and F-measure values of pleasantness classification using RASM and DASM features from each electrode pair against

Table 4

Classifiers performance by selecting RASM and DASM features from each electrode pair in response to traditional and olfaction enhanced multimedia.

Stimuli	Electrode Pair	Accuracy	MAE	RMSE	RAE	RRSE	Kappa
Traditional	$(AF7, AF8)$	65%	0.35	0.591	70	117.79	0.270
Multimedia	$(TP9, TP10)$	60%	0.4	0.632	80	125.92	0.129
Olfaction Enhanced	$(AF7, AF8)$	50%	0.5	0.707	100	141.42	0
Multimedia	$(TP9, TP10)$	70%	0.3	0.547	60	109.54	0.4

traditional and olfaction enhanced multimedia are shown in Fig. 13. We observed that features selected from $(TP9, TP10)$ pair has high precision, recall, and F-measure as compared to features selected from $(AF7, AF8)$ pair against olfaction enhanced multimedia. Whereas, features selected from $(TP9, TP10)$ pair has low recall and F-measure but high precision as compared to features selected from $(AF7, AF8)$ pair against traditional multimedia.

3.2.2. Classifier performance by selecting features from different EEG bands

Classification performance of our proposed scheme was also evaluated by selecting RASM and DASM features from individual EEG bands (delta, theta, alpha, beta, and gamma) on frontal and temporal electrode pairs for traditional and olfaction enhanced multimedia respectively (Table 5). Features selected from alpha or gamma band on $(AF7, AF8)$ electrode pair achieved the highest accuracy of 68.7% in case of traditional multimedia. Moreover, low MAE, RMSE, RAE, RRSE and high kappa values was observed for features selected from alpha and gamma bands of frontal electrode pair. Whereas, RASM and DASM features selected from delta band on $(TP9, TP10)$ pair achieved the accuracy of 75% against olfaction enhanced multimedia. Moreover, low MAE, RMSE, RAE, RRSE and high kappa values was observed for features selected from delta band of temporal electrode pair.

The classification performance of our proposed scheme was also evaluated by selecting RASM and DASM features from different combinations of EEG bands from selected electrode pairs. The classification accuracy based on combination of different EEG frequency bands features in response to traditional and olfaction enhanced multimedia using frontal and temporal electrode pairs respectively is shown in Fig. 14. We observed that combining features from different EEG bands did not improve upon the pleasantness state recognition accuracy. The highest accuracy of 68.7% was achieved by either using alpha or gamma band or combination of multiple bands in response to traditional multimedia content. Similarly, an accuracy of 75% was achieved by either using delta band or combination of multiple bands. We selected features from single EEG band (delta against olfaction enhanced multimedia and alpha or gamma against traditional multimedia) from selected electrode pair because of minimum feature vector length of 2.

4. Discussion

Some of the major studies that have classified emotional states using

EEG in response to various stimuli are summarized in Table 6. In Ref. [25], the human sense of olfaction was engaged by presenting odors as a stimuli. Frequency domain features were extracted from 256 channel EEG headset and kappa value of 0.44 was achieved to classify three (pleasant, neutral, and unpleasant) valence states. Similarly, in Ref. [26], pleasant and unpleasant odors were classified with an accuracy of 99% using 14 channel EEG headset, but only for three subjects. In Ref. [39], traditional multimedia (engaging vision and auditory senses) was used as a stimuli. Frequency domain features were extracted and two emotions (fear and relaxation) were classified with an accuracy of 92% by using a single channel EEG headset. In Ref. [40], traditional multimedia was presented as a stimuli to evoke emotions. Frequency domain features were extracted and three (positive, negative, and neutral) classes of emotions were classified with an accuracy of 73% by using 60 electrodes. In these studies, emotions were evoked and classified using EEG against a stimuli that engaged either one- or two-human senses. Whereas, tactile enhanced multimedia was presented as a stimuli engaging three (vision, auditory, and tactile) human senses [31]. Time domain features were extracted and four (happy, angry, sad, and relaxed) human emotions were classified using 4 channel EEG headband with an accuracy of 63.41%. Tactile sense was engaged with vision and auditory senses to provide an immersing environment to the participants. Whereas, our proposed system achieved an accuracy of 75% for pleasantness classification using only two frequency domain feature values.

The confusion matrices after electrode pair and EEG band selection against traditional and olfaction enhanced multimedia are shown in Table 7, which represents the individual class accuracy, sensitivity, and specificity values. Sensitivity measures the proportion of true positives, whereas specificity measures the proportion of actual negatives. We observed that the pleasant state was classified more accurately (70%) in response to olfaction enhanced multimedia as compared to traditional multimedia (55.5%). We also observed that the sensitivity and specificity for classifying pleasant class (77.7% and 72.7%) is higher for olfaction enhanced multimedia content as compared to sensitivity and specificity for classifying pleasant class (71.4% and 69.2%) using traditional multimedia content.

This study paves the way towards generation of an immersing environment and its automatic evaluation in terms of emotional responses using brain signals. We generated olfaction enhanced multimedia to simultaneously engage three (vision, auditory, and olfaction)
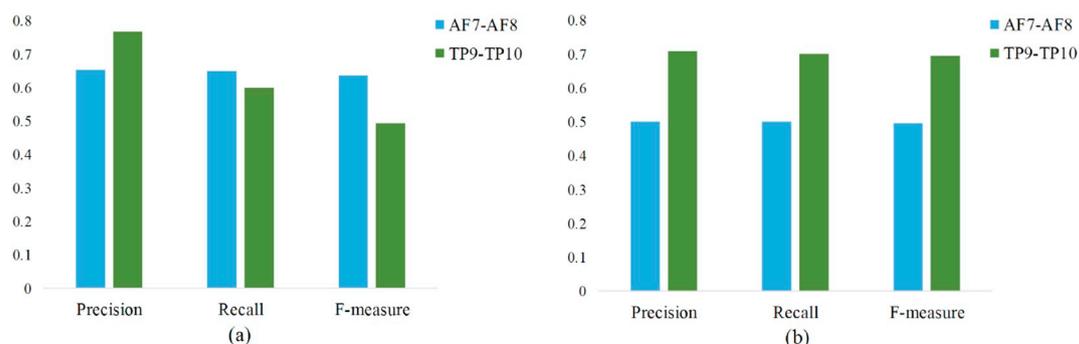

Fig. 13. Precision, recall, and F-measure for each electrode (a) traditional multimedia (b) olfaction enhanced multimedia.

Table 5
Classifiers performance by selecting features from each EEG band of selected electrode pair in response to traditional and olfaction enhanced multimedia.

| Stimuli	Electrode Pair	EEG Band	Accuracy	MAE	RMSE	RAE	RRSE	Kappa
Multimedia	(AF7,AF8)	Delta	55%	0.45	0.670	90	133.56	0.021
		Theta	40%	0.6	0.774	120	154.22	−0.290
		Alpha	68.7%	0.3	0.547	60	109.05	0.354
		Beta	40%	0.6	0.774	120	154.22	−0.290
		Gamma	68.7%	0.3	0.547	60	109.05	0.354
Olfaction Enhanced Multimedia	($TP9, TP10$)	Delta	75%	0.25	0.500	50	100	0.5
		Theta	50%	0.5	0.707	100	141.42	0
		Alpha	60%	0.4	0.632	80	126.49	0.2
		Beta	55%	0.45	0.670	90	134.16	0.1
		Gamma	70%	0.3	0.547	60	109.54	0.4
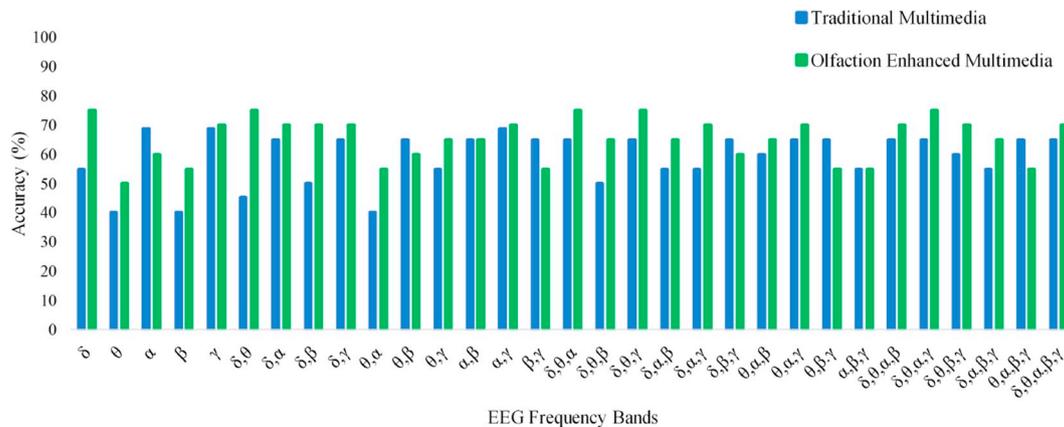
Fig. 14. Classification accuracy of the proposed scheme by selecting features from different combinations of EEG sub-bands.

Table 6
Comparison of the proposed machine learning based pleasantness classification using EEG signals with methods available in the literature.

Method	Features	No. of Channels	Emotions	Stimuli	Users (F/M)	Results
[25]	Frequency Domain	256	Pleasant, Neutral, Unpleasant	Odors	25 (9/16)	Kappa = 0.44
[26]	Frequency Domain	14	Pleasant, Unpleasant	Odors	3	Accuracy = 99%
[39]	Frequency Domain	1	Fear, Relaxation	Traditional Multimedia	8 (2/6)	Accuracy = 92%
[40]	Frequency Domain	60	Positive, Negative, Neutral	Traditional Multimedia	8 (5/3)	Accuracy = 73%
[31]	Time Domain	4	Happy, Angry, Sad, Relaxed	Traditional, Tactile Enhanced Multimedia	21 (10/11)	Traditional = 43.90%
						Tactile = 63.41%
Proposed	Frequency Domain	4	Pleasant, Unpleasant	Traditional, Olfaction Enhanced Multimedia	20 (10/10)	Traditional = 68.7%
						Olfaction = 75%
						Kappa = 0.5

human senses. Our brain activity analysis showed that with olfaction enhanced multimedia content the frontal part of brain showed more activity in multiple frequency bands, whereas for traditional content, temporal part was more activated with activity only in the alpha band. An important consideration here is that these contents activated different regions and hence were detected using EEG signals. The activation was more prominent for olfaction enhanced content and could be the reason for improved emotion classification performance.

5. Conclusion

In this study, olfaction enhanced multimedia content was generated by synchronizing olfaction dispenser with traditional multimedia content. The brain activity was recorded using a MUSE EEG headband, while engaging with both multimedia and olfaction enhanced multimedia content. Alpha, theta and delta bands were found to be more significant using *t*-test, while engaging the sense of smell in comparison to traditional multimedia content. Two valence states, which represents pleasantness were classified using SVM with an accuracy of 68.7% and 75% in case of traditional and olfaction enhanced multimedia respectively by selecting appropriate electrode pairs and EEG bands. This study directs that brain is more active while watching a content that engages the sense of smell in addition to auditory and vision senses. Accuracy improves for both stimuli by applying features and classification on

Table 7
Confusion matrices of the best accuracy case after electrode pair and EEG band selection in response to traditional and olfaction enhanced multimedia.

Stimuli	Pleasant	Unpleasant	Classified as	Accuracy	Sensitivity	Specificity
Traditional	5	4	Pleasant	55.55%	71.43%	69.23%
	2	9	Unpleasant	81.81%		
Olfaction	7	3	Pleasant	70.00%	77.77%	72.73%
	2	8	Unpleasant	80.00%		

significant bands. An enhanced sensation of reality could be achieved by generating immersing multimedia environment which enriches the human experience of viewing modern digital content. Olfaction enhanced multimedia content can be used in future for education, rehabilitation and mental health therapies.

Declaration of competing interest

Authors declare no conflict of interest.

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