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# TRANSITION OF EMOTIONS FROM THE NEGATIVELY EXCITED STATE TO POSITIVE UNEXCITED STATE: AN ERP PERSPECTIVE

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**Abstract**

The cognitive aspects like perception, problem-solving, thinking, task performance, etc., are immensely influenced by emotions making it necessary to study emotions. The best state of emotion is the positive unexcited state, also known as the High Valence Low Arousal (HVLA) state of the emotion. The psychologists endeavour to bring the subjects from a negatively excited state of emotion (Low Valence High Arousal state) to a positive unexcited state of emotion (High Valence Low Arousal state). In the first part of this study, a four-class subject independent emotion classifier was developed with an SVM polynomial classifier using average Event Related Potential (ERP) and differential average ERP attributes. The visually evoked Electroencephalogram (EEG) signals were acquired from 24 subjects. The four-class classification accuracy was 83% using average ERP attributes and 77% using differential average ERP attributes. In the second part of the study, the meditative intervention was applied to 20 subjects who declared themselves negatively excited (in Low Valence High Arousal state of emotion). The EEG signals were acquired before and after the meditative intervention. The four-class subject independent emotion classifier developed in Study 1 correctly classified these 20 subjects to be in a negatively excited state of emotion. After the intervention, 16 subjects self-assessed themselves to be in a positive unexcited (HVLA) state of emotion (which shows the intervention accuracy of 80%). Testing a four-class subject independent emotion classifier on the EEG data acquired after the meditative intervention validated 13 of 16 subjects in a positive unexcited state, yielding an accuracy of 81.3%.

Keywords: EEG, emotion, emotion transition, arousal, valence.



## 1. Introduction

Investigating a psychological aspect using electronics and measurement techniques requires the acquisition and highly structured analysis of physiological data for delineation and quantification. One such psychological aspect is emotion. Emotion is generally defined as a short and intense reaction of humans in response to a stimulus, internal or external. While the external stimulus is usually through sensory organs, internal stimulation often occurs as a result of a memory



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recall. When a person is negatively excited, his emotional state is said to be positioned in the *Low Valence High Arousal* (LVHA) quadrant of a 2-D arousal-valence plane. Anger, frustration, disgust, tension, *etc*., are a few emotions that lie in this category. The negatively excited state is supposedly the worst category of human emotional state. On the contrary, the best state of emotion is that of a positive unexcited state. The emotion of a person in a positive unexcited state is located in the *High Valence Low Arousal* (HVLA) quadrant of a 2-D arousal-valence plane. This category has emotions like calm, relaxed, at ease and glad, *etc*. The psychologists endeavour to bring the subjects from a negative excited state (LVHA) to a positive unexcited state (HVLA) of emotions. The study proposed here focuses on developing a four-class subject independent emotion classifier and its subsequent application to detect the transition of emotions from the negative excited state (LVHA) to the positive unexcited state (HVLA) of emotions. The review in Section 2 shows a number of studies undertaken to carry out the transition of emotions. The studies that validate the effect of meditation on the transition of emotions by analyzing the physiological signals collected before and after the meditative intervention are limited. The data acquisition methodology used for acquiring evoked *Electroencephalogram* (EEG) signals is explicitly described in Section 3. Section 4 describes the development of a four-class emotion classifier using *Event Related Potential* (ERP) attributes acquired from *Electroencephalogram* (EEG) signals of 24 right-handed male subjects. The four-class classification was performed using an SVM polynomial classifier. A guided meditation technique to involve progressive relaxation among the subjects is comprehensively elaborated in Section 5 of this study. The intervention is about half an hour of meditation which requires simple preparation like sitting in a silent room with minimal disturbance. The subjects who were identified to be in a negative excited state (LVHA) for any reason were voluntarily asked to undergo half an hour of meditation. We identified 20 subjects for data collection and analysis for emotion transition experiments. The pre-intervention and post-intervention data were acquired to validate the developed emotion classifier, and the results are presented in Section 6.

## 2. Literature review

The field of emotion recognition, emotion transition, and development of affective *Brain-Computer Interface* (BCI) is in vogue and has attracted biomedical engineers mainly to obtain a better *Human-Computer Interface* (HCI) to develop machines as companions, prevent cases of rage, screen out mission-critical operations and check the effects of mood-altering drugs and non-pharmaceutical interventions. Du *et al.* tested the effects of emotions (arousal and valence) on the takeover performance of drivers in a conditionally automated driving scenario and evaluated that positive valence improved the takeover quality while high arousal negatively impacted the driver's performance [1]. The necessity of testing the emotional wellbeing of pilots affected by work stress was analyzed in [2]. Viczko *et al.* found the changes in current EEG after meditation in *Augmented Reality* (AR) [3]. The results in [3] were similar to the existing study specifying that even a single session of AR meditation produced significant changes in electrophysiological resting-state activity [4]. Tarrant *et al.* focused on the importance of combining neuro-feedback with meditation. The EEG feedback was used to check the state of consciousness under meditative intervention [5]. The effect of internal and external stimulus to study the transition of emotions was analyzed in [6]. The inference regarding the transition of emotions was made using fuzzy logic. The subjects were asked to imagine the degree and charge related to each sentence. The analysis was confined to four states of emotion: Joy, Sadness, Fun, and Anger. Though a high correlation between the results of the model and the response of the subjects was obtained, no

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physiological parameters were obtained to validate the result. It would have been more interesting to see the transition from angry to joy state of emotion, but the study in [6] has not explained the transition of emotions in this manner. The sequence in which the emotional sentences were shown to the subjects was not specified.

Xiaolan *et al.* quantified the perception of subjects related to their current emotional state (reappraisal parameter) in a range of -10 to +10 to observe how the initial emotional state, current emotion-evoking stimulus, and individual personality characteristics of a subject affect the regulation and transition of emotions [7]. It was found that the emotional effect on a subject could be experiential, behavioral, and physiological. Though the defined results are significant, the validation from physiological data is missing. A similar emotion transition model was developed based on Hidden Markov Models using the Speech Under Simulated and Actual Stress (SUSAS) database [8, 9]. The study of Filipowicz [10] outlined the effects of transition of emotions in negotiations, while Van Kleef [11] outlined how and when the symmetric and asymmetric effects are produced due to the exhibition of emotions in an organization. By symmetric effects, the author means that the outcome is positive for the exhibitor when a positive emotion is expressed and the outcome is negative for the expresser when a negative expression is displayed. Similarly, the asymmetric effects indicate advantageous outcomes for the expresser when a negative emotion is displayed and disadvantageous outcomes when a positive expression is displayed. The transition of emotions does produce asymmetric effects. However, the effects of emotions other than happiness and anger need to be thoroughly reviewed [11].

Ichimura and Mera described how *Mental State Transition Network* (MSTN) could help predict the responses to an emotional stimulus. The authors tested the stepwise operation of an MSTN to calculate the transition cost (probability) associated with the transition of emotion from the current state to another. This study shows that strong intervention is required to bring the subjects from an angry state of emotion to a happy state of emotion. Using only a statement (from a story) to evoke emotions also limits the stimulating effect on subjects [12].

Xiang *et al.* described a mental state model to predict the next state of emotion. The probability of transition among seven emotion states: happy, sad, angry, disgusted, fearful, surprised, and serene was determined on the basis of an MSTN. The analysis is based on a psychological questionnaire that was presented to subjects from both Japan and China [13]. Interestingly, in the questionnaire the subjects were asked to consider themselves in one state of emotion and predict the possibility of transition to another in the absence of any external or internal stimuli. It was found that in the absence of an external stimulus, the subjects retained the previous state of emotion. Further, the results indicated that the probability of transition of emotions from LVHA state to LVLA or vice versa was higher, and the probability of transition from angry to happy emotion was lower. The researchers concluded that most likely no transition of emotional state occurs in the absence of any stimulus.

Aftanas and Golosheikin described the changes in EEG attributes obtained from *Experienced Meditators* (EM) and *Novice* (non-experienced) *Meditators* (NM). The results show EMs exhibit better psycho-emotional stability and capacity for identifying emotions than NMs. The difference in EEGs and cortical activity during meditation confirms the generation of positive emotional experiences in EM. The authors claimed that EMs exhibit a better ability to identify emotions, but it is also prudent to mention that the feedback of the subjects was taken for the calm state only [14]. To study if the meditation process causes changes in EEG signals of the subjects, Goshvarpour and Goshvarpour experimented on 25 healthy women. The EEG data were collected before and during the process of meditation. The master (an expert who guides through the meditation process) helped some of the subjects in meditation. The results displayed the variation in the state of mind before and during meditation. The effect of meditation, *i.e.*, after the meditation data also needs to be extracted and analyzed to see changes in the state of mind [15]. The proposed study in this paper analyzes the EEG data before and after the meditation process. Taking a clue from [15], we have decided to fall back on a master who helps the subjects under observation in meditation. Kimmatkar and Babu used audio, video, and thoughts to elicit emotions, but the music was used as an intervention to bring the subjects to a relaxed state. However, the initial state of emotion of the subjects was not known. The focus was more on emotion detection rather than on the transition from LVHA to HVLA state of emotion [16].

Filipowicz *et al.* discussed the effect of transition of emotion states on interpersonal (social) interactions and relational impressions. The authors found that the transition of emotion from happiness to anger leads to better results in negotiation and better relational impressions among the negotiators than when the negotiator displayed steady-state anger. It could also be concluded that the angry to happy emotional transition, as compared to the steady-state happiness, was insignificantly related to differences in negotiation outcomes but significantly related to differences in relational impressions [17]. Since the transition of emotions affects interpersonal negotiations and relations, it becomes necessary to corroborate the transition of emotions with physiological signals.

Almost all the studies on emotion transition reviewed here are based only on self-assessment of subjects, and none have corroborated their findings by acquiring and analyzing EEG or other physiological signals before and after the transition of emotions. In this proposed study, apart from developing an emotion classifier, the testing of an intervention technique has been performed by acquiring an EEG before and after the intervention.

### *2.1. Research gaps*

The researchers have contributed a lot to the classification of emotion states, but the validation of classification techniques for the subjects under study still needs to be addressed. Jenke *et al.* validated the emotion classification results of previous research using different features but left out the validation of emotion classification using ERP features [18]. It is pertinent to mention here that most of the emotion classification studies are based on power spectrum density features or statistical features acquired from single-trial or average EEG signals, but the studies based solely on average ERP for emotion classification are limited. The use of single-trial ERP features for emotion classification is even rarer. Also, the studies employing single-trial EEG features for emotion classification are mostly subject-dependent. The baseline and noise interference effects limit the online emotion classification using single-trial EEG signals. However, the multimodal analysis for affect recognition is gaining importance now [19]. In a prominent study of average ERP attributes, high arousal and valence classification accuracies were obtained at the expense of the orthogonal nature of arousal and valence domains [20]. Further, the results needed to be presented unambiguously by clearly specifying the trials classified correctly and how one classifier's inaccuracy adds to the total error count, resulting in lower overall accuracy.

As far as emotion transition is concerned, though meditation techniques have been used in experiments with the subjects, none concentrates explicitly on bringing the subjects from LVHA state to HVLA. The meditation techniques reportedly cause changes in physiological variables and the EEG, but the tasks that can cause the transition of human emotion states have not been tested through self-assessment and EEG-based emotion classifier. The MSTNs proposed so far have either been theoretical or based on individual feedback. Validation of results using the data acquired before and after the meditation is missing. In this study, the four-class subject independent emotion classifier developed on 24 subjects has been tested on evoked data acquired from 20 subjects, both before and after the emotion transition intervention.

*Metrol. Meas. Syst.,*Vol. 29 (2022), No. 2, pp. 405–423
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## 3. Data acquisition methodology, pre-processing operations, and feature extraction

The transition in emotions could be proved if we had an emotion classifier modeled on our data to detect and classify four states of emotions along arousal and valence domains. The 2-D arousal-valence plane can be divided into four quadrants: LVHA, *High Valence High Arousal* (HVHA), HVLA, and *Low Valence Low Arousal* (LVLA). The evoked EEG signals were acquired from 24 male subjects using a BIOPAC provided MP150 system to develop a four-class emotion classifier.

EEG signals were acquired in unipolar mode from the frontal electrodes Fp1, Fp2, F3, F4, Fz, and F8 with a reference electrode fitted on the left mastoid. The experiment has been approved by the University Ethics Committee, and all the subjects (all male and 24 in number) were above 18 but below 24 years old. Figure 1 shows the methodology used to acquire time-locked EEG signals [21]. The subjects were evoked by using images from the *International Affective Picture System* (IAPS) as per the mean arousal and valence ratings provided along with them [22]. The experiment was performed on two Dell i5 computers, with both the machines having 4 GB RAM, 500 GB hard disk drives, working at 3.20 Ghz clock speed. Both computers operated under the Windows 7 system. Throughout the data acquisition for emotion detection, we did not change the brightness of the display systems. All the subjects were evoked using a system with the same monitor, with the same settings, including brightness, and under the same ambient light conditions. For *low arousal* (LA)/*low valence* (LV) emotions, the IAPS images with a mean rating lower than four, and for *high arousal* (HA)/*high valence* (HV) emotions, the images with average ratings of more than six were chosen to evoke the subjects. In this manner, 40 images were selected for each class of emotion. Each visual stimulus was shown to a subject for 1s followed by a cross symbol on a white background of 1.5 s, resulting in an epoch of 2.5 s. The self-assessment of the chosen images resulted in a correlation (between assessed and given ratings for both arousal and

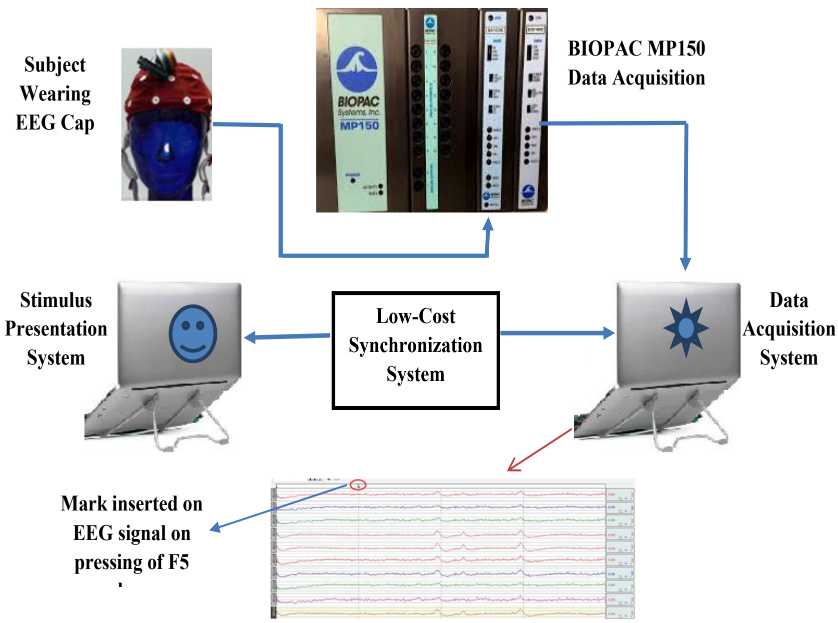


Fig. 1. Methodology of acquisition of evoked EEG signal.

valence) above 0.8 [23]. The subjects placed some of the images which failed to evoke emotions (such as Cow, Homeless man, Dishes) in the neutral zone.

The EEG signals acquired on the frontal electrodes were directed to infinite impulse response (IIR) low pass and high pass filters to bring EEG signals in the frequency range of 0.5–40 Hz. Also, a 50 Hz notch filtering operation was performed to keep the data acquisition and pre-processing operations similar to an existing study on ERPs [20]. The single-trial EEG signals thus obtained for a particular emotion class (after discarding the EEG signals corresponding to the rejected visual evoking stimulus during self-assessment) were averaged. The local maxima and minima were obtained from the averaged EEG signal at different latencies, as shown in Table 1. The acquired ERP features include P100, PT100, N100, NT100, P200, PT200, N200, NT200, P300, PT300, N300, and NT300 and the difference of ERPs P100-N100, P200-N200, and P300-N300. For example, P300 is the maximum EEG potential in the time bracket of 280-320 ms, and PT300 is the time in ms at which P300 is obtained.

Table 1. ERP features acquired from EEG signals and their nomenclature.

| **Time Bracket after the onset of the stimulus (ms)** | **ERPs acquired in the time bracket** | | **Latency at which ERP has been acquired** | | **Difference of ERP** |
|---|---|---|---|---|---|
| | **Maxima** | **Minima** | **Latency Value at which maxima have been obtained** | **Latency Value at which minima havebeen obtained** | **Maxima-Minima** |
| 80–120 | P100 | N100 | PT100 | NT100 | P100–N100 |
| 180–220 | P200 | N200 | PT200 | NT200 | P200–N200 |
| 280–320 | P300 | N300 | PT300 | NT300 | P300–N300 |

The average EEG signals corresponding to the four classes are shown in Fig. 2. To reduce artifacts due to smiling, movement of eyeballs and blinking of eyes, the corrupt data was shown to the subjects. The electrodes were tapped, the subjects were asked to blink their eyes rapidly and move them from left to right and vice versa. In this way, the subjects were apprised of how the EEG signals become corrupted due to the movement and blinking of their eyes. The subjects were asked to blink their eyes during the display of the cross symbol during the data acquisition experiment. This was done for every subject before acquiring the data.

The statistical analysis (Anova) was performed on the *Event Related Potentials* (ERP) and the latencies at which they were acquired. While performing Anova, the average ERP data from all the four classes viz. LVHA, HVHA, HVLA, and LVLA was considered with a null hypothesis that the mean of each attribute of each class was the same. The application of Anova showed that $F$ value 5.3 is greater than the $F_{\text{crit}}$ value of 2.2. This shows that the data from the four classes is significantly different. Table 2 shows a sample of different attributes. We did not use *Independent Component Analysis* (ICA) and artifact removal techniques in accordance with [18], as these operations did not reportedly impact the classification results considerably but added to offline processing time.

The classification of emotions was performed using an *support-vector machine* (SVM) polynomial classifier with 10-fold cross-validation considering the orthogonal nature of emotions along arousal and valence domains as shown in Fig. 3. The methodology used in feature selection is in line with the existing study [20]. All the features (full ERP set or difference of ERPs) were initially selected for training a subject independent emotion classifier on a particular order of SVM polynomial classifier. Accuracy of classification (*arousal*/*valence*) was determined. A new

*Metrol. Meas. Syst.,*Vol. 29 (2022), No. 2, pp. 405–423
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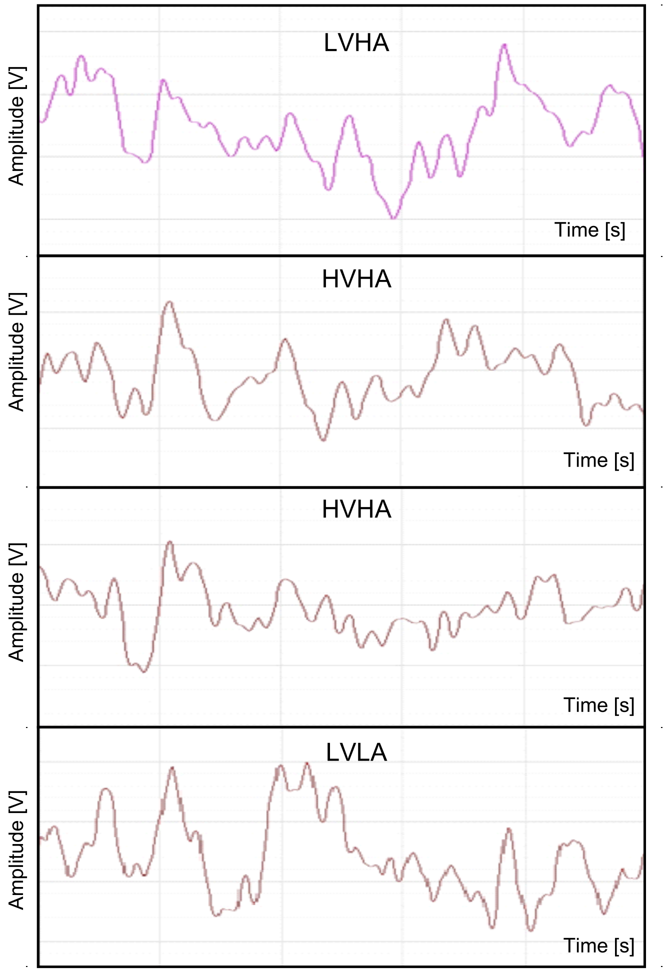


Fig. 2. Average EEG signals of 1s duration acquired from a frontal electrode.

attribute set was selected by removing one of the attributes in a preset order. The classifier was again trained and tested. If the accuracy using the new attribute set was bigger than the previous one, the new attribute set was retained, and the previous one was ignored. A new attribute set was thus generated by removing or retaining a new attribute and the accuracy using this new attribute set was compared with the previous one. The features were reduced one by one in a preset order, with each removal retained if it resulted in enhanced or sustained accuracy. This process of selecting features (and SVM polynomial order) was continued till the classification accuracy did not increase further. The same procedure was repeated for the next order of the SVM polynomial classifier. The lowest order providing the highest accuracy was chosen. Similar operations were performed using the difference of ERPs and six latencies [23, 24]. For four classes of emotions, a total of 576 samples (a few samples are shown in Table 2) were identified for emotion classification. Out of these, 100 samples (25 samples belonging to each class of emotion) were exclusively used for testing, and the remaining 476 samples were used for training

Table 2. Sample of ERP (mV) and latencies (seconds).

| P100 | N100 | P200 | N200 | P300 | N300 | PT100 | NT100 | PT200 | NT200 | PT300 | NT300 | Class of Emotion |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| –0.0029 | –0.0049 | –0.0016 | 0.00045 | 0.00045 | –0.0003 | 0.12 | 0.088 | 0.18 | 0.214 | 0.32 | 0.298 | LVHA |
| –0.003 | –0.0054 | –0.0014 | 0.00166 | 0.00166 | 0.00107 | 0.12 | 0.086 | 0.22 | 0.208 | 0.318 | 0.292 | LVHA |
| –0.0029 | –0.0053 | –0.0015 | 0.00102 | 0.00102 | 0.00055 | 0.12 | 0.088 | 0.22 | 0.206 | 0.28 | 0.298 | LVHA |
| –0.0026 | –0.0047 | –0.0011 | 0.00037 | 0.00037 | –0.00029 | 0.12 | 0.088 | 0.18 | 0.214 | 0.28 | 0.298 | LVHA |
| 0.00526 | 0.004 | 0.00418 | 0.0007 | 0.0007 | –0.00256 | 0.118 | 0.092 | 0.18 | 0.22 | 0.28 | 0.318 | HVHA |
| 0.00507 | 0.0038 | 0.00417 | 0.00198 | 0.00198 | –0.00125 | 0.12 | 0.092 | 0.18 | 0.21 | 0.28 | 0.318 | HVHA |
| 0.00487 | 0.00382 | 0.00402 | 0.00145 | 0.00145 | –0.00176 | 0.118 | 0.092 | 0.18 | 0.206 | 0.28 | 0.318 | HVHA |
| 0.00507 | 0.00363 | 0.00385 | –0.0002 | –0.0002 | –0.0032 | 0.12 | 0.092 | 0.18 | 0.218 | 0.28 | 0.318 | HVHA |
| 0.00212 | 0.00148 | 0.00414 | 0.0024 | 0.0024 | 0.00036 | 0.086 | 0.114 | 0.204 | 0.18 | 0.28 | 0.32 | HVLA |
| 0.00247 | 0.00185 | 0.00433 | 0.00348 | 0.00348 | 0.00125 | 0.08 | 0.112 | 0.22 | 0.18 | 0.28 | 0.32 | HVLA |
| 0.00235 | 0.00172 | 0.0044 | 0.003 | 0.003 | 0.00096 | 0.082 | 0.11 | 0.22 | 0.18 | 0.28 | 0.32 | HVLA |
| 0.00218 | 0.00145 | 0.00414 | 0.00175 | 0.00175 | –0.00168 | 0.08 | 0.116 | 0.202 | 0.18 | 0.28 | 0.32 | HVLA |
| –0.0003 | –0.0016 | –0.0028 | –0.0042 | –0.0042 | –0.00474 | 0.08 | 0.11 | 0.22 | 0.2 | 0.28 | 0.312 | LVLA |
| 0.00028 | –0.0009 | –0.0018 | –0.0023 | –0.0023 | –0.00331 | 0.08 | 0.11 | 0.22 | 0.192 | 0.28 | 0.312 | LVLA |
| 0.00018 | –0.0011 | –0.002 | –0.003 | –0.003 | –0.00394 | 0.08 | 0.11 | 0.22 | 0.19 | 0.28 | 0.31 | LVLA |
| –0.0003 | –0.0019 | –0.0034 | –0.0058 | –0.0058 | –0.00601 | 0.08 | 0.112 | 0.184 | 0.212 | 0.32 | 0.304 | LVLA |

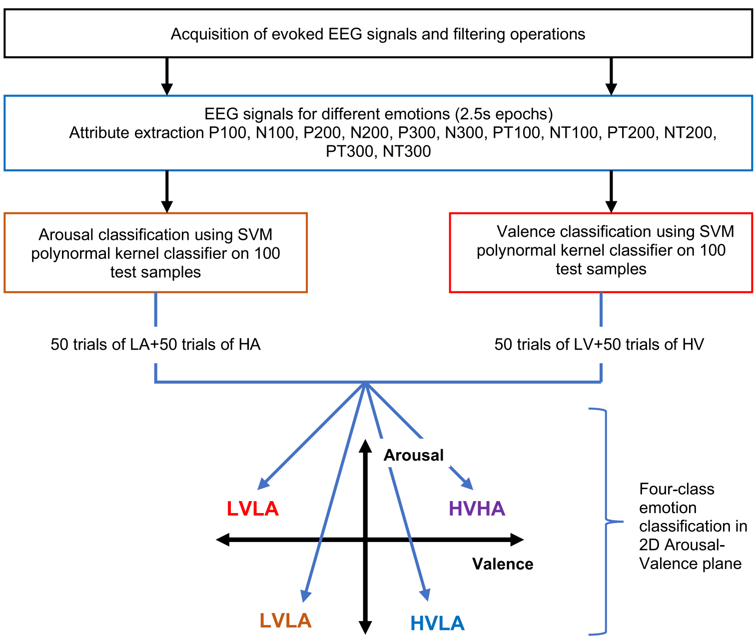


Fig. 3. Methodology used for the development of an emotion classifier.

*Metrol. Meas. Syst.*,Vol. 29 (2022), No. 2, pp. 405–423
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and cross-validation. In other words, 476/576, *i.e.*, 82.64% of data was used for training, while 17.36% (100/576) was used exclusively for testing. These 100 samples were randomly selected. Further, it is worth mentioning that the data used for testing was never used for training and cross-validation of the classifier. The data analysis is in line with subject independent emotion classification of single-trial ERP attributes [25]. For a particular order of SVM polynomial (say 3), the training was performed on nine folds at a particular value of $C$, and testing was performed on the remaining fold of the data. The average accuracy was determined for all the tests performed on 10 folds, and if average accuracy was greater than or equal to the best accuracy, the current value of $C$ was chosen as the best value of $C$ and the best accuracy as the current accuracy obtained on the best $C$. This process was repeated on the other values of $C$. The classifier modeled on this polynomial order, best $C$, and the training data was tested on the 100 test samples that were not a part of the dataset used for cross-validating and training of the classifier.

## 4. Emotion classification results on frontal electrodes

The methodology describing classification methodology is shown in Fig. 3. The classification accuracy obtained for arousal and valence using average ERP attributes was 88% (at SVM polynomial order 6) and 94% (at SVM polynomial order 4). This orthogonal classification model generated a four-class classification of 83%, which is better than in the existing studies. The confusion matrix for four-class emotion classification results and the error analysis are shown in Table 3 and Table 4, respectively.

Table 3. Four-class confusion matrix obtained for frontal electrodes using average ERPs.

| **Confusion Matrix** | | **Predicted Classes** | | | |
|---|---|---|---|---|---|
| | | **LVHA** | **HVHA** | **HVLA** | **LVLA** |
| Actual Classes | LVHA | 22 | 2 | 0 | 1 |
| | HVHA | 1 | 23 | 1 | 0 |
| | HVLA | 1 | 3 | 21 | 0 |
| | LVLA | 6 | 0 | 2 | 17 |

Table 4. Error analysis of results on average ERPs.

| **Error Analysis** | **Sensitivity (%)** | **Specificity (%)** | **Precision (%)** | **Negative Predictive Value (%)** | **F1 Score (%)** |
|---|---|---|---|---|---|
| LVHA | 88.0 | 89.3 | 73.3 | 95.7 | 80.0 |
| HVHA | 92.0 | 93.3 | 82.1 | 97.2 | 86.8 |
| HVLA | 84.0 | 96.0 | 87.5 | 94.7 | 85.7 |
| LVLA | 68.0 | 98.7 | 94.4 | 90.2 | 79.1 |

The arousal and valence classification was 86% and 90% (at SVM polynomial orders 3 and 6) using differential ERP attributes, resulting in a four-class classification accuracy of 77%. The confusion matrix and error analysis of the four-class results are shown in Table 5 and Table 6.

The comparison of results with existing studies is shown in Table 7.

Table 5. Four-class confusion matrix obtained for frontal electrodes using the difference of average ERPs.

| **Confusion Matrix** | | **Predicted Classes** | | | |
|---|---|---|---|---|---|
| | | **LVHA** | **HVHA** | **HVLA** | **LVLA** |
| Actual Classes | LVHA | 20 | 1 | 0 | 4 |
| | HVHA | 1 | 19 | 5 | 0 |
| | HVLA | 1 | 2 | 19 | 3 |
| | LVLA | 2 | 0 | 4 | 19 |

Table 6. Error analysis of results on differential average ERPs.

| **Error Analysis** | **Sensitivity (%)** | **Specificity (%)** | **Precision (%)** | **Negative Predictive Value (%)** | **F1 Score (%)** |
|---|---|---|---|---|---|
| LVHA | 80.0 | 94.7 | 83.3 | 93.4 | 81.6 |
| HVHA | 76.0 | 96.0 | 86.4 | 92.3 | 80.9 |
| HVLA | 76.0 | 88.0 | 67.9 | 91.7 | 71.7 |
| LVLA | 76.0 | 90.7 | 73.1 | 91.9 | 74.5 |

The proposed subject independent classifier in this study is better in performance as compared to those described in the existing studies using images as visuals to evoke emotions. If we compare our study with [20], our results are better on account of electrode selection, order of SVM polynomial classifier, and feature reduction. The advantage of the emotion classification technique used in this research study is that it is simple with only filtering operations involved as pre-processing operations. It uses very few attributes for developing an emotion classifier such that any EEG electrode among the used could provide data for testing. This advantage has been used and the classifier developed on frontal electrodes has been used for validating the transition of emotions. Frontal electrodes have been found to be useful for the classification of positive and negative emotions in [38]. However, selecting only those epochs which relate well with the particular emotion as in [39] can further improve classification results.

As compared to the previous study on ERP [23], the emotion classifier was developed using the evoked data acquired from the three central electrodes, namely Fz, Cz, and Pz. The four-class classification accuracy lay between 75–76.8% for the average and difference of average ERP attributes. These results are lower than the accuracy results presented here in this study. The best results in [24] were 83%, but by using three emotion classifiers all modeled at different SVM polynomial orders. For other classification models developed in [24], the four-class emotion classification accuracy remained lower than 83% as obtained in this study. It is pertinent to mention over here that the aim of this study is to develop a subject independent emotion classifier and test it on the EEG data acquired before and after the intervention to bring the subjects from a negatively excited state of emotion (LVHA) to positive and unexcited state of emotion (HVLA). This application of the developed emotion classifier on the data acquired before and after the intervention validates the classifier's effectiveness. [40–43] show that the physical properties of visuals, such as the brightness, contrast, and color composition can affect the behavioral response of the subjects. Eroğlu *et al.* analyzed the perceptual effect of visual stimuli on brain responses by changing the brightness of IAPS visuals used for evoking emotions. The variations in the average power of the acquired EEG signals with an increase in the brightness of pleasant,

Table 7. Comparison of proposed results with existing studies.

| Reference, Stimulus, No. of subjects | Classifier (Number of classes classified), Features Used | Results |
|---|---|---|
| [26], IAPS, 4 | FDA, NB, (2), Power and statistical features | Average accuracy – 55%<br>(Best results using FDA and EEG) |
| [27], IAPS, eNTERFACE 2006 data [28] and 10 other subjects | SVM, ANN, NB, (5, 3 and 2), ERD/ERS, cross correlation, peak frequency and Hjorth parameters | Results using SVM (5 classes) 31% along valence and 28% along arousal<br>Results using SVM (3 classes) 37% along valence and 49% along arousal<br>Results using SVM (2 classes) 72% along valence and 68% along arousal |
| [20], IAPS images, 14 Males and 14 Females | SVM Polynomial and MD (4), ERP and Event Related Oscillations | Arousal – 82.1%<br>Valence – 85.7%<br>81.25% using SVM and 79.46% using MD |
| [29], GAPED pictures [30] and classical music, 10 | Gaussian SVM with LOTO-CV and LOSO-CV (2), PSD | Subject independent – 63.67%,<br>Subject dependent – 70.55%<br>(average accuracies) |
| [31], IAPS, 26 | SVM, (2), Power | 96.15%–100% (Best with RFE) |
| [18], IAPS, 16 | QDA with diagonal covariance Estimates, (5), Time domain and frequency domain features | 32%–43%,<br>(Average of 5 feature selection techniques) |
| [32], IAPS, 10 | IQK-SVM, ISVM, kNN, SVM, (2), PSD | (Best average accuracies using IQK-SVM)<br>Arousal – 84.8%, Valence – 82.7% |
| [33], IAPS, 30 | SVM, (2,3,4, and 5), Hjorth parameters in time-frequency domain | 2 class accuracy – 70% (Subject Independent Best Results) |
| [34], GAPED, 12 | PSD, SP, CSP, (2), LDA | Subject independent accuracy along valence – 66.74% |
| [35], 2-D IAPS and 3-D Scenario pictures, 60 | SVM LOSO and SVM RFE, (2) Time domain and frequency domain features from ECG, Power spectrum from EEG | Arousal (Total average accuracy) – 75%<br>Valence (Total average accuracy) – 71.21% |
| [36], Oasis dataset [37], 25 | k-NN, ANN, RF, SVM, LR, (2), Spatial and frequency features | Valence (Subject independent) – 80.2%<br>Valence (Subject dependent average accuracy) – 96.1%<br>(Best Results) |
| **Proposed study** | SVM, (4), Average and Differential average ERP | Arousal – 88% (average ERP) and 86% (differential ERP)<br>Valence – 94% (average ERP) and 90% (differential ERP)<br>Four class – 83% (average ERP) and 77% (differential ERP) |

*FDA, Fisher Discriminant Analysis; NB, Naïve Bayes; SVM, Support Vector Machine; GNB, Gaussian Naïve Bayes Classifier; ANN, Artificial Neural Network; ERD, Event-Related Desynchronization; ERS, Event-Related Synchronization; MD, Mahalanobis Distance; GAPED, Geneva Affective Picture Database; LOTO-CV, Leave One Trail Outcross Validation; LOSO-CV, Leave One Subject Outcross Validation; PSD, Power Spectral Density; RFE, Recursive Feature Extraction; QDA, Quadratic Discriminant Analysis; IQK-SVM, Imbalanced quasiconformal kernel SVM; kNN, k-Nearest Neighbors; SP, Signal Power; CSP, Common Spatial Pattern; LDA, Linear Discriminant Analysis; ECG, Electrocardiogram; RF, Random Forest; LR, Logistic Regression.

neutral, and unpleasant images were noticed [43]. During emotion classification experiments, it is generally advised not to repeat the visuals as the prior exposure to stimuli would impact the true momentary reactions of the subjects. Further, according to [42, 44], the IAPS images were labeled as outdated compared to the modern standards of picture quality (*i.e.*, brightness, contrast, and color composition) and recommended the use of the combination of stimulus taken from the IAPS, GAPED [30], and the Nencki Affective Picture System (NAPS) [45] for emotion evocation. It is prudent to mention that in this proposed study, emotion classification has been carried out without considering the brightness bias of visuals used for evoking emotions. No photo enhancement or any change in the physical display of the photo was applied while obtaining the SAM rating from the subjects and, consequently, the same picture was used to acquire the evoked EEG signals to eliminate any changes.

## 5. Data acquisition for the transition of emotions (pre- and post-intervention)

The EEG signals were acquired from 20 subjects twice, before the meditative intervention and after it. All the subjects were right-handed male subjects. The subjects visited the experiment room on different days spanning three months. Among these 20 subjects, seven subjects overlapped with the study on the development of an emotion classifier. Since the emotions are short and intense, we tried to attain the pre- and post-meditative intervention EEG from two frontal electrodes, F3 and F4 in the shortest time possible. It is worth mentioning here that the protocol followed for EEG acquisition and processing operations (filtering) on the EEG data acquired before and after the meditative intervention is the same and also similar to the data acquisition methodology for emotion classification, as shown in Fig. 1. The ERP features were acquired in response to neutral images. A neutral image such as a plus symbol on a white screen was shown for 1 second, followed by a cross symbol on a white screen for 1.5 seconds. The epoch time of 2.5 seconds was fixed in line with the emotion recognition methodology discussed in the emotion classification. The images were taken from online sources and are shown in Fig. 4.

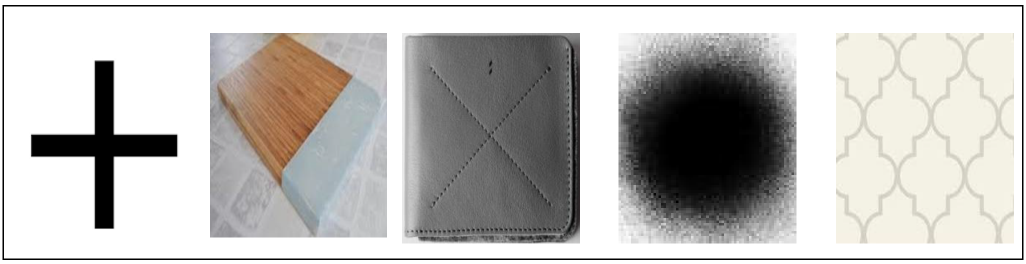

Fig. 4. Neutral images used for EEG acquisition.

The neutral images were chosen keeping in view the response of subjects to IAPS images. During data acquisition, these neutral images were presented in random order. The EEG signals (before and after the meditative intervention) from each subject were acquired in twenty trials, *i.e.*, each neutral image was shown four times to the subject. The EEG signals lasting less than 1 minute were acquired from each subject. From the averaged EEG signals, the ERP and latency features, namely P100, N100, P200, N200, P300, N300, PT100, NT100, PT200, NT200, PT300, and NT300 were determined.

In the premeditative intervention mode, the EEG signals were acquired from those subjects who declared (self-assessed) themselves to be of tense/angry/frustrated, *i.e.*, negatively excited (LVHA) state of mind. We played a screeching sound so that the subjects did not get settled and become neutral during the pre-meditation data acquisition. After the pre-meditation signal acquisition, the self-assessment of subjects was taken. The subjects who assessed themselves to be in a negatively excited (LVHA) state of emotion went through the meditative intervention. An audio file in the mp3 format was played. The audio file guided the subjects to perform some simple meditative tasks and helped them achieve a calm state of mind. It was ensured that the subjects were not disturbed by any external activity during an intervention. Some of the excerpts from the guided intervention are described below. The first four tasks are auxiliary tasks to prepare the subjects for meditation. The main intervention starts with Step 5. The methodology of the research also assumes that it is advised that meditation is not performed through reading these steps as it requires a thorough demonstration and close monitoring by properly trained meditation experts.

**Preparatory Steps**

1. Feel your breathing by putting a hand on your stomach.
2. Feel the heartbeat by putting your right hand on the heart.
3. Feel the pulse on your left wrist by using your right hand.
4. Produce the sound "OOOOOOOM," and at this point in time the distance between your teeth should be paper-thin.

**Meditation Steps**

5. Close your eyes, stretch your legs and relax your body
6. Monitor your body parts relaxing, including fingers, neck, *i.e.*, the whole body is relaxing.
7. Think I am the happiest person in the world.
8. Keep smiling and feel your breath without making any noise.
9. Feel the depth of your breath as you breathe in.
10. Observe your breath coming deeper and slower, relax and smile.
11. Inhale relaxation and exhale out your worries, problems, and negativity.
12. Feel freshness and continue to breathe in at your own pace.
13. Observe the breathing speed to be going down.
14. Witness the thoughts coming to your mind. Don't stop them but resist them.
15. Tell your thoughts "All lines to this route are busy."
16. Place your right hand on your heart and feel your heartbeat.
17. Put your heartbeat to productive and positive deeds.
18. Monitor the breathing. Inhale positivity and exhale positivity. Keep smiling.
19. Monitor your pulse on your left-hand wrist using your right hand.
20. Count your pulse, keeping your eyes closed.
21. Count till 50. (Here, there is pin-drop silence for about a minute)
22. Put your hands on your ears and listen to the sound of silence, and after a few minutes, listen back to me. (Again, there is pin-drop silence for about two minutes)
23. The next task is you are supposed to inhale and produce the sound "OOOOOOOM" with your hands on the ears. Repeat it ten times.
24. Move your hands down, inhale, and produce the sound "OOOOOOOM" with little space in your teeth. Repeat it ten times.
25. Relax and keep smiling. Keep your eyes closed. Your mind is most receptive now.
26. Again produce the sound "OOOOOOOM" with your teeth at a very close distance but with hands on your ear. Repeat it ten times.
27. Put your hands down, relax; your brain is fresh now.
28. Again monitor your breath. I am calm, and I am relaxed.
29. Keep your eyes closed. (After a countdown from 20 to 1) Open your eyes and observe silence for as long as you can.
30. Feel your emotions and maintain silence. The meditation is over.

Each subject assessed his emotions after the intervention. The EEG signals post meditative intervention were acquired in a similar manner as discussed before by using neutral stimulus as shown in Fig. 4. The ERP features shown in Table 1 were acquired for classification using the SVM polynomial classifier developed above using average ERPs. The classifier model is subject-independent and is based on absolute average ERP attributes obtained from frontal electrodes.

## 6. Emotion classification results on pre-intervention and post-intervention data

The ERP features acquired for both pre-meditative and post-meditative intervention cases from two frontal EEG electrodes were tested using SVM polynomial classifiers developed on average ERP attributes of frontal electrodes. On analyzing the test data of subjects acquired before the meditative intervention, the output of the classifier matched with the self-assessment for 20 subjects, *i.e.*, these 20 subjects were placed in an LVHA state through both self-assessment and EEG classifier. After the meditative intervention, one subject reported being in a negatively excited (LVHA) state of emotion, three subjects reported themselves in an HVHA state of emotion, and 16 subjects reported being in a positive unexcited state (HVLA) in self-assessment after meditation. The intervention efficacy is thus 80%. According to self-assessment, the subject's emotions placement on an arousal-valence scale before and after the meditative intervention is shown in Fig. 5. It can be seen from Fig. 5 that 16 subjects assessed themselves to be in a positive unexcited state (HVLA) after the intervention. On application of the emotion classifier on the data of these 16 subjects, 13 subjects were correctly classified in the HVLA state, two subjects in the LVLA, and one in the HVHA quadrant of the arousal-valence plane. This gives a classification accuracy of 81.3%. Among the remaining four subjects, one was correctly classified in the LVHA state of emotion, and two were predicted correctly in the HVHA state of emotion. Thus, the proposed classifier has validated the post meditative intervention in 20 subjects. The confusion matrix is shown in Table 8 and the error analysis in Table 9. The results of the classifier application in subjects before and after the meditative intervention are also shown in Fig. 6.

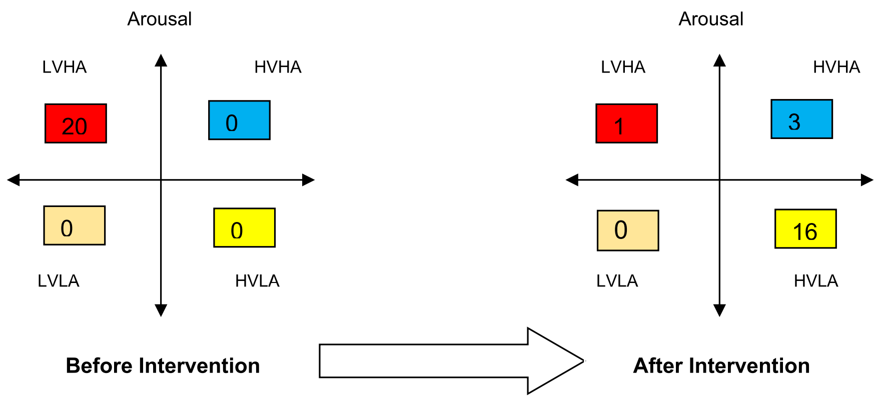


Fig. 5. Effect of a meditative intervention on emotions of subjects.

Table 8. Confusion matrix obtained on subjects with post meditative intervention.

| **Confusion Matrix on F3 and F4 Electrodes** | | **Predicted Classes** | | | |
|---|---|---|---|---|---|
| | | **LVHA** | **HVHA** | **HVLA** | **LVLA** |
| Actual Classes | LVHA | 1 | 0 | 0 | 0 |
| | HVHA | 1 | 2 | 0 | 0 |
| | HVLA | 0 | 1 | 13 | 2 |
| | LVLA | 0 | 0 | 0 | 0 |

*Metrol. Meas. Syst.*, Vol. 29 (2022), No. 2, pp. 405–423
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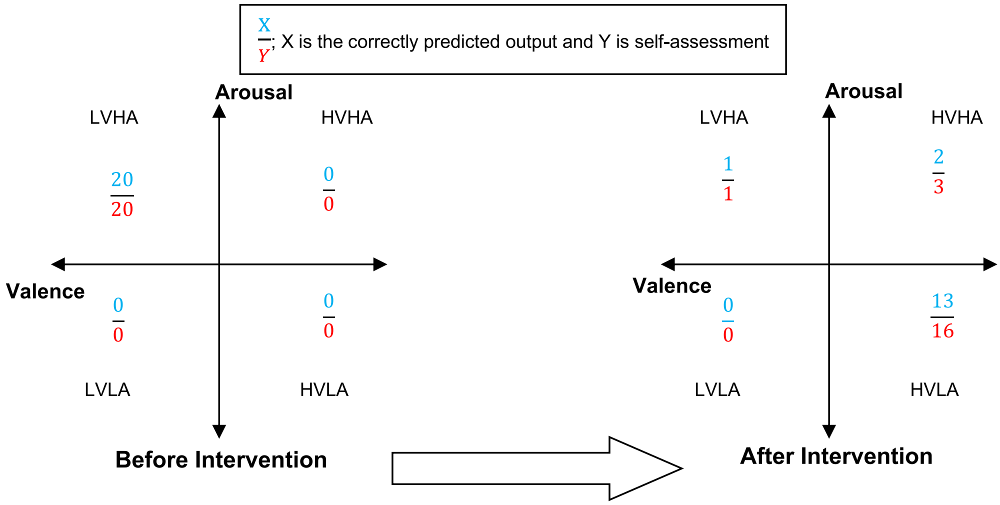


Fig. 6. Classifier results before and after the meditative intervention for emotion transition.

Table 9. Error analysis for results in Table 8.

| Error Analysis | Sensitivity (%) | Specificity (%) | Precision (%) | Negative Predictive Value (%) | F1 Score (%) |
|---|---|---|---|---|---|
| LVHA | 100.0 | 94.7 | 50.0 | 100.0 | 66.7 |
| HVHA | 66.7 | 94.1 | 66.7 | 94.1 | 66.7 |
| HVLA | 81.3 | 100.0 | 100.0 | 57.1 | 89.7 |

## 7. Conclusions

Emotion classification using EEG signals can primarily be performed offline by taking the average of EEG signals acquired from several trials or online by taking a single trial. In this study, emotion classification has been obtained by taking the average of EEG signals. Apart from ERP features, the difference of ERPs has been used to develop subject-independent four-class emotion classifiers. The four-class emotion classification accuracy using average ERP features is 83%, being 77% while using the difference of average ERP features. In all the cases, we have considered self-assessment as a gold standard for training, testing, and validation of the four-class emotion classifier. The existing study of average ERPs [20] reported four-class emotion classification accuracy of 68–82% with mid-range accuracy of 75%, whereas, in the proposed classifier, the four-class emotion classification accuracy lies between 82–88% with a mid-range of 85%. The proposed classifier is better in performance on account of electrode selection, order of SVM polynomial classifier, and feature reduction.

The developed emotion classifier has been validated by applying it to the emotion transition data. An intervention technique has been applied on 20 right-handed male subjects. These 20 subjects had been found to be in a negative excited state (LVHA) of emotion using self-assessment and EEG classifier. The intervention was given to these 20 subjects to bring them to a positive unexcited state (HVLA) state. Of the 20 subjects, 16 could comply with the intervention and reported (through self-assessment) the transition to a positive unexcited state (HVLA) state. Application of a four-class subject independent emotion classifier validated 13 of 16 subjects in positive unexcited state (HVLA) state, which is more than 81%.

It is prudent to mention here that the subject-dependent emotion classifier requires training each time the subject is to be tested for emotion because of the day-to-day variations in external and internal conditions. This limits its practical utility. The subject independent classifier is trained through collecting several trials on different days from a large number of subjects possessing unique behavior and personality. Thus, once trained, a subject-independent classifier would have more practical utility in classifying emotions without training again before testing on subjects.

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