Affect Recognition Using EEG Signal

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***Abstract*—Emotion states greatly influence many areas in our daily lives, such as: learning, decision making and interaction with others. Therefore, the ability to detect and recognize one's emotional states is essential in intelligence Human Machine Interaction (HMI). The aim of this study was to develop a new system that can sense and communicate emotion changes expressed by the Central Nervous System (CNS) through the use of EEG signals. More specifically, this study was carried out to develop an EEG-based subject-dependent affect recognition system to quantitatively measure and categorize three affect states: Positively excited, neutral and negatively excited. In this paper, we discussed implementation issues associated with each key stage of a fully automated affect recognition system: emotion elicitation protocol, feature extraction and classification. EEG recordings from 5 subjects with IAPS images as stimuli from the eNTERFACE06 database were used for simulation purposes. Discriminating features were extracted in both time and frequency domains (statistical, narrow-band, HOC, and wavelet entropy) to better understand the oscillatory nature of the brain waves. Through the use of k Nearest Neighbor classifier (kNN), we obtained mean correct classification rates of 90.77% on the three emotion classes when K equals 5. This demonstrated the feasibility of brain waves as a mean to categorize a user's emotion state. Secondly, we also assessed the suitability of commercially available EEG headsets such as Emotive Epoc for emotion recognition applications. This study was carried out by comparing the sensor location, signal integrity with those of Biosemi Active II. A new set of recognition performance was presented with reduced number of channels.**

I. Introduction

Affect computing has been an active research topic in the past two decades and has shown a strong growth in the past few years. It aims to narrow the communication gap between humans and machines. With the advancements of the human computer interface, there is an inevitable need for machines to understand and react to the affect state of the user. Even though the definition of affect itself is a topic of debate within the psychological literature, it is globally accepted that affects such as moods and emotional states significantly influence the outcomes of people's daily activities in learning and decision making. The basic goal behind most affect computing systems is to automatically detect, recognize and respond adaptively to the affect state of a person as human-human interactions will do.

With recent advancements in embodied sensor technology, affordable wireless EEG headsets with dry-electrodes have become available for leisure use to the general public, which are able to capture the electric potentials of neuronal populations through electrodes resting on the scalp. Affect sensitive applications are being developed in fields such as gaming, health-care and learning technology. During the learning process, subjects experience various emotions such as satisfaction, happiness or frustration and sadness. The emotional states of a learner can significantly affect the outcome of the learning process. If a computer interface can recognize and adapt to such emotion changes as a class teacher would do by changing the material presented or the way it was presented, it will positively impact the learning gain and improve the overall learning experience.

From the health care perspective, an appropriate assessment of the patient's emotional state during treatments or hospital stays could provide valuable insights to the recovery process and the treatment options. Incorporating such minimally invasive bio-feedback application into wireless handheld devices can also provide an alternate means for emotion communication to people who are challenged in conventional communication means, such as functional autism groups. It can also provide invaluable cues for care-givers and teachers for continuous daily social behavior monitoring.

An overview of a fully automated emotion recognition system utilizing EEG signal is shown in Fig. 1. In the learning stage, labeled EEG signals were used to extract features both in time and frequency domains for the event-related characteristics of EEG signals. To better understand the association between various affect states and their EEG oscillatory pattern, four feature extraction algorithms were tested. The effectiveness of the features were evaluated in the testing stage by comparing their correct recognition rates using two classification methods.

A. Emotion Representation and Models

Affect expression is a result of complex interactions of the biological nature with the surrounding environment based on observation, personal experience, and self-regulation, a detailed discussion on the correlation or causality relationship between emotion and core affect was discussed in [1]. Due to the multiple attributions of emotion, to model such multi-facet

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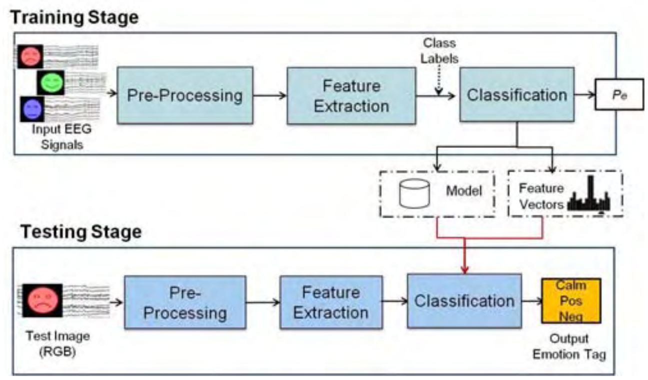

Fig. 1. System Diagram

process has long been a very challenging, if not impossible, problem.

A circumplex model of emotion that was based on Cognitive Theory [2], [3] is shown in Fig. 2 where emotions are represented in a 2D plane, with one dimension (x-axis) for judged Valence which stands for one's judgment about a situation as positive or negative and the other dimension (y-axis) for Arousal spans from calmness to excitement, expressing the degree of one's excitation. For empirical study, this model provides a simplified representation of human emotions and is more suitable for emotion analysis using physiological signals [3]. More importantly, this 2D model has been proved to be consistent with self assessment scores during emotion elicitation experiments [1]. Therefore, for the rest of the paper, we will refer to this model as our definition of discrete regions of emotion states.

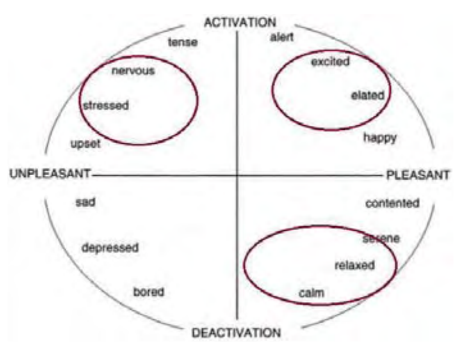

Fig. 2. Circumplex Models of Emotion

According to this model, high arousal can be interrelated as highly motivated, high valence means the current situation is pleasant and approachable, whereas low valence is unpleasant, avoidable. Hence, in the domain of learning, decision making and behavior monitoring, we would like to know when the person is happy ('positively excited'), or frustrated ('negatively excited'), or bored ('calm'). In this study, we have focused our work on the recognition of these three key affective states.

B. Affect Detection and Physiological Signals

Changes in biological signals are related to many psychological constructs and it is of great importance to distinguish such differences in the literature of Affect Computing. There is a many-to-many mapping between psychology and physiological changes, which makes affect detection a very challenging problem. Physiological signals such as Electrocardiogram (ECG), Galvanic Skin Response (GSR) and Blood Volume Pressure (BVP) have been widely studied as suitable means for recognizing affects through the use of appropriate pattern recognition techniques. However, current emotion recognition results obtained from the above physiological signals are often challenged or flawed, due to the difficulty in justifying the collected physiological data consists the intended emotion during experiments. Also, if the emotional information does exist, it is usually induced from multiple sources (visual stimuli and personal experiences), therefore such emotion recognition approaches still have a lot of work ahead. Moreover, the previously mentioned physiological signals originate from the Autonomous Nervous System (ANS), which can also affected by the change of physical activities.

EEG emotion recognition is a relatively new topic that is being actively studied in the community of Affect Computing. EEG signals are generated from the Central Nervous System (CNS)and directly reflects the brain activity, which can potentially overcome the undesired physiological signal variations resulted from non-emotional physical or environmental changes (such as galvanic skin response). EEG signals collected from multiple channels with correlated information can potentially produce a more reliable and robust emotion recognition system.

Previous EEG studies [4], [5] generally suggest that frontal asymmetry is correlated with the affect states; greater activation of the right frontal lobe accompanies the experience of more negatively valenced emotions, whereas greater left frontal activation accompanies the experience of more positively valenced experiences. This knowledge was used as ground information in the process of channel reduction analysis.

II. Experimental Setup and Signal Acquisition

Since the objective of this study was to address the classification of three affect states, we made use of the publicly available Emobrain database that was recorded during eNTERFACE06 workshop and was specifically designed for detecting the above three affective states. Data were collected from 5 participants, aged from 22 to 38, using the Biosemi Active II system for three different sessions, with 30 trials per session. Each trial consisted of a block of five images selected for the same affect class to ensure stability of the emotion over time. Each picture was displayed on the screen for 2.5 seconds leading to a total of 12.5 seconds per block. Blocks of different classes were displayed in random order to avoid participant habituation. The total number of observations obtained was $5 \times 3 \times 30 = 450$. EEG signals were recorded using 64 surface electrodes sampled at 1024 Hz. However, due to the parallel recording of fNIRS signals, the final EEG recordings consists of signals from only 54 electrodes. (64 less the following ten frontal electrodes: $F5$, $F8$, $AF7$, $AF8$, AFz, $Fp1$, $Fp2$, Fpz, $F7$, $F6$, due to the simultaneous placements of fNIR sensors). The experimental protocol is detailed in Fig. 3, more details can be found in [6].

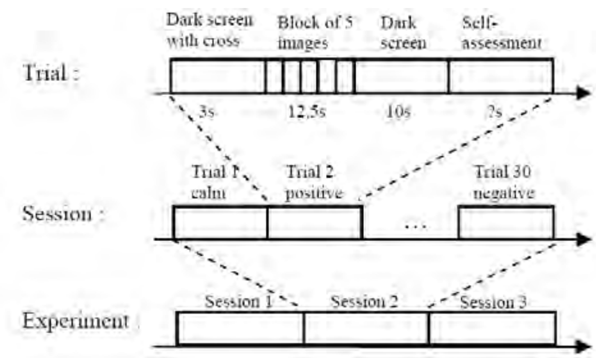

Fig. 3. Protocol description for eNTERFACE06-EMOBRAIN database

For emotion elicitation, participants were stimulated using images selected from the International Affective Picture System (IAPS)[7]. The selection of the three images subsets, corresponding to the emotional states of interest was based on the imperial thresholds on the valence and arousal scores shown in Table II.

$$
\begin{aligned}
calm: &\quad \overline{arousal} < 4; < 4\overline{valence} < 6 \\
positive \quad exciting: &\quad \overline{valence} > 6.8; \\
&\quad Var(valence) < 2; \\
&\quad \overline{arousal} > 5 \\
negative \quad exciting: &\quad \overline{valence} < 3; \overline{arousal} > 5
\end{aligned}
$$

This selection resulted in 106, 71, and 150 pictures respectively for the above three classes and shown in Fig. 4.

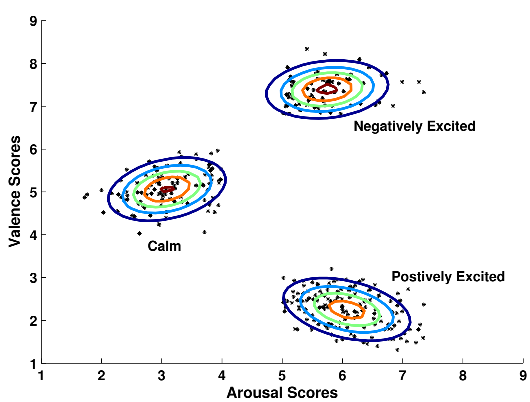

Fig. 4. Selected IAPS images for the 3 classes emotion elicitation experiment

A. Ground Truth Validation

Emotion is known to be very subjective and dependent on social context and previous experience [1]. However, emotion consistency across participants is important in designing a generalized emotion recognition system. One can never be sure that the person feels the emotion that was intended by the pictures; and a self-assessment gives a good estimation whether the pictures evoked similar emotions among participants.

For this experiment, participants were asked to self-assess their emotions on a simplified version of the SAM (Self-Assessment Manikin) scale. Since the SAM scores were obtained after the projection of 5 images taken from the same class, a new set of IAPS scores were computed as the mean value of the IAPS scores for the 5 images in that trial. In order to understand the relationship between the self assessments and the IAPS scores, we calculated the Pearson correlation coefficients for the two variables, valence and arousal. The averaged Pearson correlation coefficient between the IAPS scores and SAM scores is $.754$ for the valence dimension, and $.817$ for the arousal dimension. These values show that the correspondence between the expected emotion and the experienced emotion is very good, and that the images do evoke the desired emotion most of the times.

TABLE I
PEARSON CORRELATION COEFFICIENT BETWEEN IAPS SCORES AND SELF ASSESSMENTS PER PARTICIPANT

	Correlation Valence	Correlation Arousal
P1	0.6994	0.9387
P2	0.6286	0.8628
P3	0.6550	0.6583
P4	0.9816	0.8533
P5	0.8057	0.7716

Further examination of the self assessment inputs from Participant 2 and Participant 5 has shown that their inputs in each trial for the valence and arousal are mostly equal, and have a variance around 1 between the two variables. However, it might be an very hard task to quantize one's emotion according to the 2D model, for example, some persons tends to give extreme scores where others always choose the center. This does not mean that the participants didn't experience the emotion, it simply implies that he/she was having trouble to 'express' the emotion (*which is indicated with the correct recognition rate, shows the existence of an emotion state*). Also from the application point of view, self-assessment inputs may be not always possible to obtain, such as people with autism disorder. Therefore, due to the above reasons, we used the IAPS scores for the final labeling of the data.

III. Signal Preprocessing and Feature Extraction

The preprocessing step is directly related to the type of features that will be extracted in the next step. Data preprocessing typically serves two purposes: firstly to reduce artifact inferences caused by muscle movements such as eye blinking, body movements or power line interference ($> 60Hz$). Secondly, for some feature extraction algorithms III-B, data is required to be de-trended or standardized. For example, the wavelet methods requires data to be zero-mean and unite variance, and the HOC algorithm requires the data to be zero mean, which will be discussed in details in the next section.

In [8], it was shown that event-related EEG oscillation pattern changes are expressed mostly in the spectral components that resides within the Alpha ($8-13Hz$), and Beta ($13-30Hz$) bands. Other bands such as the Delta band (up to $4Hz$) contains mostly noise such as pulses, neck movement, and eye blinking. Beta waves are connected to an alert state of mind, whereas alpha waves are more dominant in a relaxed person. Therefore, to preprocess the input EEG signals, a Butterworth 10th order band-pass filter ($8-30Hz$) was applied to the collected EEG signals to extract the Alpha and Beta waves. The order of the Butterworth filter was chosen by the minimum order required to meet the constraints such that no more than 3dB loss within the passband and at least 60dB attenuation in the stopband.

A. Time Domain Feature Extraction

Features were extracted in both time domain and frequency domain to emphasize on two aspects of the EEG signals: the oscillatory nature and event evoked potential variations. For the signal analysis in the time domain we used the following two type of features:

1) Statistical-based Features
The statistical features proposed by Picard[9] for physiological signals were used here to form the proposed FVs, which were defined as ($X_t, t = 1, ..., N$ is the raw N-sample EEG signal) given in the following. The mean of the raw signals μ_x, the standard deviation of the raw signals σ_x, the mean of the absolute values of the first differences of the raw signals δ_x, the mean of the absolute values of the first differences of the normalized signals $\overline{\delta}_x$, the mean of the absolute values of the second differences of the raw signals γ_x, and the mean of the absolute values of the second differences of the normalized signals $\overline{\gamma}_x$.
2) Higher Order Crossings
Observed time series of physiological signals such as EEG, display both local and global up and down movements. Characteristics of the oscillatory mode process discrimination powers and can be extracted as features for classification purpose. To extract the HOC features, EEG signals (detrended) are subject to a 6th order IIR Butterworth bandpass filter with the frequency range of $8-30Hz$, which covered the conventional alpha and beta waves.
The oscillation behavior, seen in a finite zero-mean time series $Z_t, t = 1, ...N$ can be expressed through the zero-crossing count. When a specific sequence of filters is applied to a time series, the corresponding sequence of zero-crossing counts is obtained, resulting in the so-called HOC sequence [10]. Let $Z_1, Z_2, ..., Z_N$ be a zero-mean stationary time series, the zero-crossing count in discrete time is defined as the number of symbol changes in the corresponding clipped binary time series [10]

$$X_t = \begin{cases} 1, if Z_t \geq 0 \\ 0, if Z_t < 0 \end{cases} \quad (1)$$

The number of zero-crossings, denoted by D, is defined in terms of X_t

$$D = \sum_{t=2}^{N} [X_t - X_{t-1}]^2, 0 \leq D \leq N-1 \quad (2)$$

HOC combines ZC counts and linear operations: the difference operator is a linear high-pass filter

$$\nabla Z_t \equiv Z_t - Z_{t-1} \quad (3)$$

and the squared gain of the second difference ∇^2 is a more pronounced high-pass filter.

B. Spectral Domain Features

For the analysis in the spectral domain, we also used two type of features:

1) Wavelet Features
A new methodology was proposed by [11] on feature extraction from standardized raw EEG signals (zero mean, unit variance) to estimate the signal energy and entropy in the wavelet space. In particular, Discrete Wavelet Transform (DWT) [12] using the Daubechies eighth-order orthonormal bases ($db8$)was employed and the extracted wavelet coefficients at the lth scale, given by $C_X(l, n)$ for S scales

$$ENG_l = \sum_{n=1}^{2^{S-l}-1} |C_X(l, n)|^2, \quad (4)$$

$$ENT_l = -\sum_{n=1}^{2^{S-l}-1} |C_X(l, n)|^2 \, log(|C_X(l, n)|^2), \quad (5)$$

$$N = 2^S, 1 < l < S.$$

The parameters of Eq. 4 and Eq. 5 were used as a feature vector, i.e., $FVw = [ENG_l, ENT_l]$.
To define the scales of decomposition, we refereed to the scale and frequency relationship in Discrete Wavelet Transform (DWT)shown in [13]and at each decomposition scale frequency range is halved. For example, with a sampling frequency of $1024Hz$, the alpha and beta waves ($8-30Hz$)resides within the decomposition levels 5-6 inclusively.
2) Narrow-band Energy Event related energy variation within the alpha and theta waves were calculated here as features. In particular, frequency components within $8-30Hz$ were divided into 2 Hz sub-bands and the energy within each sub-bands were used as features for classification as shown in Fig. 5. The use of narrow frequency bands reduces the danger that frequency specific effects go undetected and was further discussed in [8].

IV. Simulation Results and Discussion

Since the EEG feature sets, are of very high dimensionality (thousands of features) compared to the number of samples in the sets (450 per trial or 2250 per image, depending on the classification scheme), it is believed there is always a linear

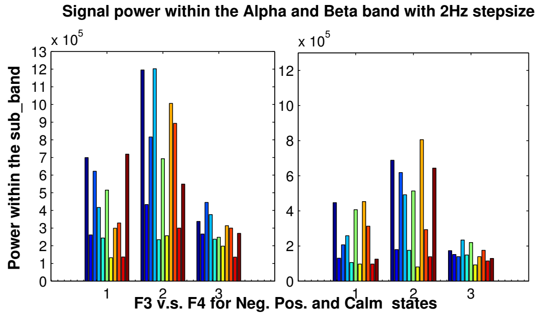

Fig. 5. Power within sub bands for $F3$, $F4$ for Negative Positive and Calm states

boundary that can completely separate training samples of the different classes. Another advantage of using linear classifiers is that they give better generalized solutions. However, in the high dimensional EEG feature space, a exponentially larger sample size is required to have a meaningful statistical analysis [14]. Linear classifiers such as Linear Discriminating Analysis (LDA) on a small sample size would run into the singularity problem and feature reduction mechanisms need to be used to solve the sparsity of the samples in the high dimensional feature space. The choice of feature reduction methods can greatly affect the recognition rate later on, which makes it harder to compare the effectiveness of the selected features on representing the variations of EEG signals under emotion stimuli. We opted for a non-linear classification method without feature reduction to avoid error propagation due to such feature reduction methods. In the case when the feature dimension is comparable to the number of samples available, LDA was also applied to test the feasibility of a linear classifier.

K Nearest Neighbors (kNN) classifier with Euclidean distance as a distance metric was used here, and odd number of neighbors $1, 3, 5, 7, 9$ were picked to avoid ties, however, similar results would be obtained with even numbers when majority rule was used for nearest points tie breaking. kNN is an instance based method. By increasing the number of neighbors, the effect of artefacts are reduced within classes, but the class boundary between classes are also enlarged, which could potentially degrade the classification performance. Therefore, the final recognition performance is most depends on the class separation in the feature space.

5-fold cross validation process was carried out to test the robustness of our system and also to overcome the sample size problem, at each folder, 80% of the samples were used for training and 20% of the samples for testing. Simulation results shown in Table II were generated using both kNN and LDA classifier on the specified features without applying feature reduction algorithms.

A. Subject-Specific Emotion Recognition

The following table shows recognition rate using all the Electrodes.

TABLE II
EMOTION RECOGNITION RATES USING ALL 54 ELECTRODES AND 5NN

Participants	Statistical	Narrow-bands Power	HOC	Wavelet
P1	87.67	82.67	96.33	62.67
P2	88.67	90.00	97.00	91.67
P3	86.22	84.22	93.33	75.11
P4	88.00	93.33	93.33	88.224
P5	83.56	88.22	97.78	76.67

Based on the above results, we performed a sensitivity test on the kNN classifier. We examined how well kNN performs with varying number of Neighbours, $K = 1, 3, 5, 7, 9$, using HOC features.

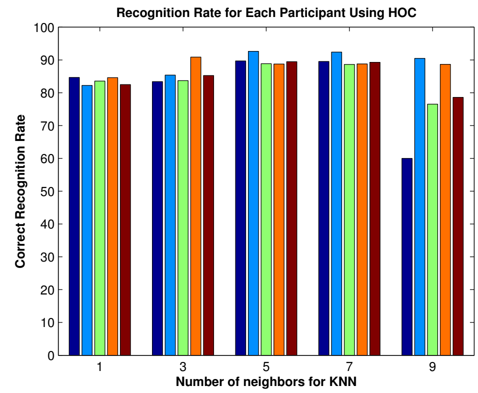

Fig. 6. Recognition Rate using HOC features for K = 1,3,5,7,9

As we can see, the recognition rate is rather stable with varying number of neighbours, this shows that the three emotion classes were well separated in the feature space and a linear classifier is suitable for this classification as well.

B. Subject-Dependent Emotion Recognition

TABLE III
EMOTION RECOGNITION RATES USING ALL 54 ELECTRODES

Classifier	Statistical	Narrow-bands Power	HOC	Wavelet
5NN	81.39	82.62	90.77	77.44
LDA	57.59	60.10	N/A	54.72

C. Reduction of Channels

The EEG recordings from the eNTERFACE06 project was collected using Biosemi Active II, a EEG cap that has 64 different channels and was designed for medical applications. Emotive epoch is a commercially available, wireless neuro headset with 14 EEG channels. As is shown in Table IV, the Emotiv Software Development Kit (SDK) for research includes a 14 channel (plus CMS/DRL references, $P3/P4$ locations),high resolution and provides wirelessly neuro-signal acquisition and processing.

However, because both caps use a standardized electrode placement according to the 10-20 system, by comparing the location of the electrodes, we were able select a set of

TABLE IV
DEVICE SPECIFICATIONS

Device	Biosemi Active 2	Emotive EPOC SDK
Data Format	EDF	MAT
Resolution	24 bits ADC	16 bits (14 bits effective)
Sampling Rate	1024Hz	128 SPS (2018 Hz internal)
Channels	64	14
Channels in common	$AF3$, $F7$, $F3$, $FC5$, $FC6$, $F4$, $F8$, $AF4$	

EEG channels that are present in both device, and obtain classification results using features extracted from the common channels. However, further examine the signal collected from Biosemi Active II, we also dropped $F7/F8$ which seemed to contain only thermal noise. Table Vshows the recognition rate with EEG channels that are present in both devices.

TABLE V
SUBJECT SPECIFIC RECOGNITION RATES USING 6 ELECTRODES AND 5NN

Participants	Statistical	Narrow-bands Power	HOC	Wavelet
P1	86.33	84.33	93.67	61.67
P2	86.00	89.33	98.33	89.67
P3	83.33	86.44	95.11	74.89
P4	88.67	90.44	97.33	88.00
P5	83.33	86.44	96.89	78.89

D. Subject-Dependent Emotion Recognition

TABLE VI
SUBJECT DEPENDENT RECOGNITION RATE USING ONLY 6 ELECTRODES

Classifier	Statistical	Narrow-bands Power	HOC	Wavelet
5NN	82.31	83.64	89.33	76.10
LDA	58.26	62.26	N/A	56.51

The results shown in Table VI are near identical to the results in Table III with significantly reduced number of electrodes. These results provided evidence on the feasibility of consumer grade headsets for real-time, emotion recognition in mobile applications. (the frontal asymmetry of EEG recordings by comparing recognition rate for signals obtained using selected electrodes comparing to the recognition results obtained when all electrodes were used.

V. CONCLUSION/FUTURE WORK

In this paper, we investigated a variety of techniques for feature extraction and classification to recognize affective states from EEG signals. EEG signals were acquired in three different affective states and two pattern recognition methods have been tested: k-Nearest Neighbour (kNN), Linear Discriminant Analysis (LDA). Recognition rates of above 90% were achieved for HOC features with kNN classifier using all 54 channels. By applying channel reduction, recognition results of 89.3% were achieve HOC features and kNN classifier. Our recognition rates are much higher than those achieved previously (51%)by [15] on the same database.

The present protocol for off-line acquisition of physiological signals is very close to those encountered in the BCI community so that the conclusions drawn from this study may also have some impact in this direction. An emotion elicitation task can then be regarded as a mental task that the user tries to perform in order to communicate his/her feelings. This can be useful for severely disabled people that cannot directly express their emotions. Furthermore, we have shown that with significantly reduced number of channels, classification rates maintained a level that is feasible for emotion recognition. Thus current BCI paradigms to integrate consumer electronics such as smart hand-held device with commercially available EEG headsets is promising and will significantly broaden the application cases. For the future studies, larger data sets will be utilized to investigate the impact of the number of samples per subject, the number of EEG channels and the number of emotion classes on the classification rate.

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