# Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals*

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**Abstract.** The arousal dimension of human emotions is assessed from two different physiological sources: peripheral signals and electroencephalographic (EEG) signals from the brain. A complete acquisition protocol is presented to build a physiological emotional database for real participants. Arousal assessment is then formulated as a classification problem, with classes corresponding to 2 or 3 degrees of arousal. The performance of 2 classifiers has been evaluated, on peripheral signals, on EEG's, and on both. Results confirm the possibility of using EEG's to assess the arousal component of emotion, and the interest of multimodal fusion between EEG's and peripheral physiological signals.

## 1 Introduction

Emotions pervade our daily life. They can help us guide our choices, avoid a danger and they also play a key role in non-verbal communication. Assessing emotions is thus essential to the understanding of human behavior. Emotion assessment is a rapidly growing research field, especially in the human-computer interface community where assessing the emotional state of a user can greatly improve interaction quality by bringing it closer to human to human communication. In this context, the present work aims at assessing human emotion from physiological signals by means of pattern recognition and classification techniques.

### 1.1 Emotion Models

In order to better analyze emotions, one should know the processes that lead to emotional activation, how to model emotions and what are the different expressions of emotions. Three of the emotions viewpoints that Cornelius [1] cites are the Darwinian, cognitive and Jamesian ones. The Darwinian theory suggests that emotions are selected by nature in term of their survival value, e.g. fear exists because it helps avoid danger. The cognitive theory states that the brain is the centre of emotions. It particularly focuses on the “direct and non reflective” process, called appraisal [2], by which the brain judges a situation or an event as good or bad. Finally the Jamesian

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theory stipulates that emotions are only the perception of bodily changes such as heart rate or dermal responses ("I am afraid because I shiver"). Although controversial, this later approach emphasizes the important role of physiological responses in the study of emotions.

These different theories lead to different models. Inspired by the Darwinian theory, Ekman demonstrates the universality of six facial expressions [3]: happiness, surprise, anger, disgust, sadness and fear. Emotions however are not discrete phenomena but rather continuous ones. Psychologists therefore represent emotions or feelings in an n-dimensional space (generally 2- or 3-dimensional). The most famous such space, originating from cognitive theory, is the 2D valence/arousal space. Valence represents the way one judges a situation, from unpleasant to pleasant; arousal expresses the degree of excitement felt by people, from calm to exciting. Cowie used the valence/activation space, which is similar to the valence/arousal space, to model and assess emotions from speech [4], [5]. Although such spaces do not provide any verbal description, it is possible to map a point in this space to a categorical feeling label. In the present study it was chosen to model emotions in the valence/arousal space, because this representation seems closer to real feelings, and gives the possibility to extract emotion labels from a continuous representation.

### 1.2 Emotion Expression and Analysis

Emotions can be expressed via several channels and various features can be analyzed to assess the emotional state of a participant. Most studies focus on the analysis of facial expressions or of speech ([5], [6]). These types of signals can however (more or less) easily be faked; in order to have more reliable emotion assessments, we preferred to use spontaneous and less controllable reactions as provided by physiological signals. Physiological signals can be divided into two categories: those originating from the peripheral nervous system (e.g. heart rate, ElectroMyogram -EMG, Galvanic Skin Response-GSR), and those coming from the central nervous system (e.g. ElectroEncephalograms-EEG). In recent years interesting results have been obtained with the first category of signals ([7], [8], [9]). Very few studies however have used the second category [10], even though the cognitive theory states that the brain is heavily involved in emotions [2]. Moreover, to our knowledge fusion of peripheral and EEG signals has only been studied for verbal emotion classes in [11] and for arousal in [12].

In this study, classification techniques are used on features extracted from physiological signals to assess the arousal dimension of emotions. Section 2 describes how an emotional database was constructed. Section 3 presents the classification methodology. Section 4 discusses the results obtained and stresses the interest of EEG's alone as well as fused with other physiological signals in emotional assessment.

## 2 Data Collection

This section details the creation of a database of physiological features patterns and associated labels corresponding to the underlying valence/arousal model of emotions.

This requires to elicit physiological emotional responses, to define a precise protocol to acquire the data and finally to extract relevant features.

### 2.1 Emotion Elicitation

A prevalent method to induce emotional processes consists of asking an actor to feel or express a particular mood. This strategy has been widely used for emotion assessment from facial expressions and to some extent from physiological signals [8]. However, even if actors are known to deeply feel the emotion they try to express, it is difficult to insure physiological responses that are consistent and reproducible by non-actors. Furthermore, emotions from actor-play databases are often far from real emotions found in everyday life.

The alternate approach for inducing emotions is to present particular stimuli to an ordinary participant. Various stimuli can be used such as images, sounds, videos [7] or video games. This approach presents the advantages that there is no need for a professional actor and that responses should be closer to the ones observed in real life.

In this study we used a subset of images from the 700 emotionally evocative pictures of the IAPS (International Affective Picture System [13]). Each of these images has been extensively evaluated by north-Americans participants on a nine points scale (1 - 9), providing valence/arousal values as well as ensemble means and variances. Experimentation showed a 0.8 correlation with evaluations performed by Europeans [14]. However, as observed during experiments, feelings induced by an image on a particular participant can be very different from the ones expected. This is likely due to difference in past experience. Self-assessment of valence/arousal was therefore performed in the present study by each participant and for each image.

### 2.2 Acquisition Protocol

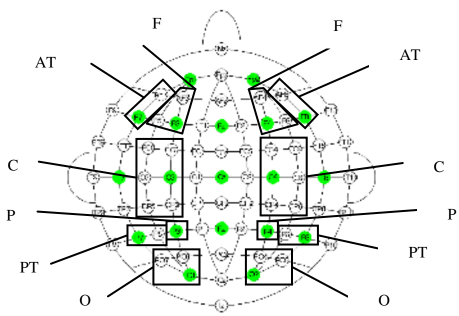
We acquired data from 4 participants, 3 males, 1 female, aged from 28 to 49. One of the participants is left handed. For EEG's we used a Biosemi Active Two device [15] with 64 electrodes (plus 2 for reference). The other sensors used were a GSR sensor, a plethysmograph to measure blood pressure, a respiration belt to evaluate abdominal and thoracic movements, and a temperature sensor. All signals were sampled at a 1024 Hz rate.

For each experimental recording, the participant equipped with the above sensors was sitting in front of a computer screen in a bare room relatively immune to electromagnetic noise. A dark screen was first displayed for 3 seconds to “rest and prepare” the participant for the next image. A white cross was then drawn on the screen center for a random period of 2 to 4 seconds, to attract user's attention and avoid accustoming. An IAPS image was subsequently displayed for 6 seconds, while at the same time a trigger was sent for synchronization. Finally, the participant was asked to self assess the valence and the arousal of his/her emotion using a simplified version of the Self Assessment Manikin (SAM [16]), with 5 possible numerical judgments for each dimension (arousal and valence). This self-assessment step was not limited in time to allow for a resting period between images.

To study the arousal dimension of emotions, 50 images of high arousal (ie. where mean arousal is greater than 5.5) and 50 images of low arousal (ie. where mean arousal is lower than 3) were presented to participants, with a relatively uniform distribution of valence. A similar experiment with valence was performed for future analysis (ongoing work).

### 2.3 Preprocessing and Features Extraction

The mechanisms and timings of temporal synchronization of emotional responses are still not well known [2]. Assuming that the maximal latency (due to the GSR signal) is about 3 to 4s, we compute all features from a 6s epoch with no particular synchronization alignment between the different signals. EEG signals were first preprocessed by bandpass filtering to keep frequencies in the 4-45Hz range. This allowed to remove power line noise as well as to preserve the 6 EEG frequency bands presented in Fig. 1.These bands were chosen according to Aftanas et al. [17] who showed a correlation between arousal elicited by IAPS images, and responses in those frequency bands at particular electrodes locations (Fig. 1, from [17]). Eyeblinks were identified as high-variance parts and removed by subtraction from the signal.




| *EEG feature* | *Location area* | *Frequency band* |
|---|---|---|
| *1* | *[PT;P;O]* | *θ1 (4-6Hz)* |
| *2* | *[PT;P;O]* | *θ2 (6-8Hz)* |
| *3* | *[PT;P;O]* | *γ(30-45Hz)* |
| *4* | *[AT;F]* | *α2 (10-12Hz)* |
| *5* | *[AT;F;C]* | *β1 (12-18Hz)* |
| *6* | *[C;PT;P;O]* | *β3 (22-30Hz)* |

**Fig. 1.** Top head view with EEG electrode locations and corresponding frequency bands

Power values of 6s epochs of these 6 frequency bands were then computed for each electrode. As several electrodes are located in the same area (e.g. 6 electrodes in area PT, P, O), the power over all these electrodes were averaged yielding a total of 6 features for the EEG's (e.g. feature one is the average power in band θ1 over all electrodes in areas PT, P, O). Most of the features concern the Occipital (O) lobe, which is not surprising since this lobe corresponds to the visual cortex and subjects are stimulated with pictures.

Concerning peripheral signals, heart rate (number of heart beats per minute) was estimated from the blood pressure signal by computing its continuous wavelet coefficients (CWT) at an empirically determined scale and then identifying maxima of the CWT by simple derivation. Each maximum then corresponds to a heart beat. The 5 peripheral signals to analyze are therefore: GSR, blood pressure, heart rate, respiration and temperature. From each of these signals were determined the following features over the 6s epoch: mean, variance, minimum and maximum, except for heart rate for which only mean and variance were used. A total of 18 features was thus obtained for the peripheral signals.

In summary, two features vectors were computed for each trial: $\mathbf{X}_{EEG}$ containing 6 EEG features, $\mathbf{X}_{peripheral}$ composed of 18 features from peripheral signals. As there were 100 trials (one per image) for the arousal assessment tests, the following classification experiments operated on 100 such pairs of feature vectors per participant.

## 3 Arousal Assessment by Classification

The determination of the participant's arousal from the extracted physiological signals is achieved by classification. Classes obtained from these signals, that correspond to various degrees of arousal, were compared with ground-truth classes constructed either based on the IAPS arousal judgment, or on the participant's self-assessment. Two classifiers were tested: naïve Bayes and a classifier based on Fisher Discriminant Analysis (FDA). It is also important to note that due to inter-participant variation, classifiers need to be trained and evaluated for each participant separately. Methods are presented in this section while results are discussed in Section 4.

### 3.1 Ground-Truth Classes Construction

The images used for the arousal assessment were purposely chosen to be of either very low or very high IAPS arousal values, that is they essentially should have belonged to 2 classes. For this reason, when using the IAPS judgments as a basis to build ground-truth classes, it was natural to divide data into two sets, one for the calm emotions and the other for the exciting emotions. In this way, two well balanced ground-truth classes of 50 patterns each were obtained.

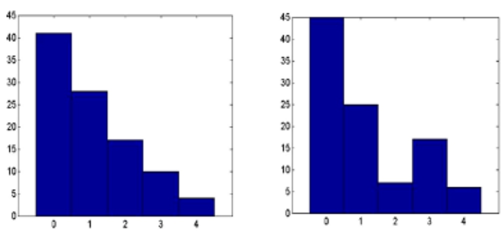



**Fig. 2.** Histograms of the self-assessments of participants 1 (left) and 4(right) on the modified SAM scale (from 0, calm, to 4, exciting)

It is more difficult to determine classes from the self-assessment values. As shown by the histograms of Fig. 2, the evaluations are not equally distributed across the 5 choices and in particular do not readily correspond to 2 classes. This can be due to the difficulty of self-assessing (or understanding) arousal, and/or to a large variability of the arousal judgments. Taking this into account, two different classification experiments based on the self-assessment were done:

- with 2 ground-truth classes, were the calm class contained patterns judged in the calmest category and the exiting class the others,

- with 3 ground-truth classes (calm, neutral, exciting) were the calm class corresponded to the first of the 5 judgment values, the neutral class to the second and third, and the exciting class to the last two.

Both labelings led to unbalanced classes, especially for the 3-classes problem: the exciting class contained very few samples (6 to 23 depending on the participant).

### 3.2 Classification

A Naïve Bayes classifier was first applied for each participant. This classifier is known to be optimal in the case of complete knowledge of the underlying probability distributions of the problem. This is unfortunately not the case in our study, since very few samples are available to construct them; a performance decrease is thus unavoidable. Further, this approach would require conditionally independant features. Finally, classification strongly depends on the à-priori probabilities of class appearance; the issue of unbalanced classes should be handled, which was done for the three classes experiment by imposing an à-priori probability of 1/3. For the sake of comparison, classification based on FDA was also performed.

Due to the rather limited number of patterns, a leave one out cross validation was preferred to a k-fold strategy in order to maximize the size of the training set. For each of the N=100 patterns of the database for a given participant, the classifiers are trained on N-1 patterns and tested on the remaining one. This was repeated N times. Results presented in the next section are the percentage of well classified examples for those N training/testing cycles. Features used were either based on EEG alone, on peripheral signals alone, or on fusion of these two modalities by concatenation of the features vectors: $X_{Fusion} = [X_{EEG}X_{peripheral}]$.

## 4 Results and Discussion

When using the 2 ground-truth classes defined according to the IAPS judgment, the Bayes average accuracy exceeded the chance level only for EEG features (54% vs. 50%). The FDA classifier performed slightly better, with 55%, 53% and 54% for EEG, physiological and fused features respectively. This is likely due to large differences between the IAPS values and the actual emotion felt by the participant. We concluded that in our experimental setting the IAPS arousal judgments could not be recovered from actual physiological measurements, and had to use self-assessments.

Results with ground-truth classes obtained from self-evaluations are presented in Fig. 3. The percentage of well classified patterns for the four participants (S1 to S4) and the average across participants are shown. Compared to the IAPS judgment, accuracies on self-assessment are higher, especially for participants 2 and 3 (see first row of Fig. 3). This tends to confirm that physiological signals better correlate with self assessment of emotion than with IAPS judgments. The best performance of 72% is obtained by using the EEG signals of participant 2 and a Bayes classifier. A similar result is obtained with the FDA (70%), which stresses the importance of using EEG signals for emotional assessment.

Fig. 3, second row, shows results for the three class problem. Again, participant 2's EEG features yield the best result of 58% of well classified patterns (compared to a chance level of 33%). Participant 4 is still the worst. Participant 1 obtains better results with a Bayes classifier than with a FDA. Extreme results for participants 2 and 4 can be explained by a better or worse understanding of the self assessment procedure. Participant 2 had a good knowledge about emotions, and was likely to accurately evaluate his feelings. On the other hand, participant 4 had difficulties in understanding what arousal was during data acquisition.

On average, EEG's signals seem to perform better than other physiological signals. The FDA over-performs Bayes' when concatenating features. This could be explained by the intrinsic FDA dimensionality reduction. Finally, the results presented showed that EEG's can be used to assess emotional states of a user. Also, fusion provides more robust results since some participants had better scores with peripheral signals than with EEG's and vice-versa.

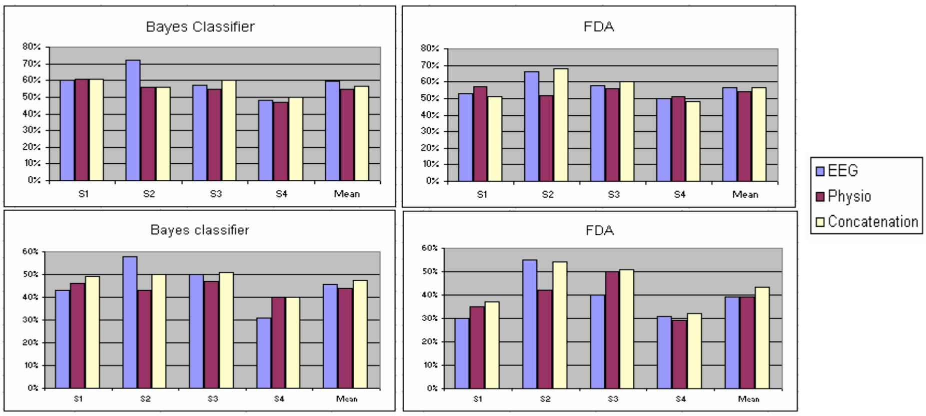



**Fig. 3.** Classifiers accuracy with 2 (top row) or 3 (bottom row) classes from self-assessment

## 5 Conclusion

In this paper two categories of physiological signals, from the central and from the peripheral nervous systems, have been evaluated on the problem of assessing the arousal dimension of emotions. This assessment was performed as a classification problem, with ground-truth arousal values provided either by the IAPS or by self-assessments of the emotion. Two classifiers were used, Naïve Bayes or based on FDA.

Results showed the usability of EEG's in arousal recognition and the interest of fusion with other physiological signals. When fusing EEG and peripheral features, the improvement was better with FDA than with the Bayes classifier. Results also markedly improved when using classes generated from self-assessment of emotions. When trying to assess emotion, one should avoid using predefined labels but rather ask for the user's feeling.

Future work on arousal assessment will first aim at improving on the current results by using non-linear classifiers, such as Support Vector Machines. Feature selection and more sophisticated fusion strategies will also be examined, jointly with the examination of other features such as temporal characteristics of signals that are known to be strongly implied in emotional processes. The next step will be the assessment of the valence component of emotion to be able to identify a point or a region in the valence / arousal space.

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