

# Extraction of valence and arousal information from EEG signals for emotion classification

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## Abstract

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Emotions play a powerful role in social influence. The ability to recognize emotion in social interactions and communication is very useful. Thus the automatic emotion recognition becomes more and more important in human – computer interaction (HCI), like psychotherapy applications, tutoring systems, marketing applications, etc.

In this project a database of recorded EEG signals is used. The subjects were looking at different images during the recording. The images were chosen to provoke emotions.

Different methods of feature extraction and classifiers are presented and discussed. Some of them were selected to build an emotion recognition system. Different wavelets for the discrete wavelet transform (DWT) are chosen as the feature extractions and the multi layer perceptron as a classifier.

Based on the dimensional emotion model, negative versus positive arousal and negative versus positive valence was tried to be classified. The results is shown, that around 2 third of the samples can be correctly classified and the obtained results are similar to other works on this database.

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## 1 Introduction

Emotion plays a powerful role in social interactions and communication. Thus the interest of automatically recognition of emotions becomes more and more important. The goal of this project is to study and understand the database, then to extract features from this database and finally to classify them to recognize emotion, simplified by an emotion model. The process of emotion recognition is shown in the following figure.

From the several presented feature extraction the wavelet transform is used, because all frequency bands of interest are covered. With the multi layer perceptron classifier the two classes arousal positive versus arousal negative and the two classes valence negative versus valence positive were tried to be classified. Overall around two third of the samples were correctly classified.

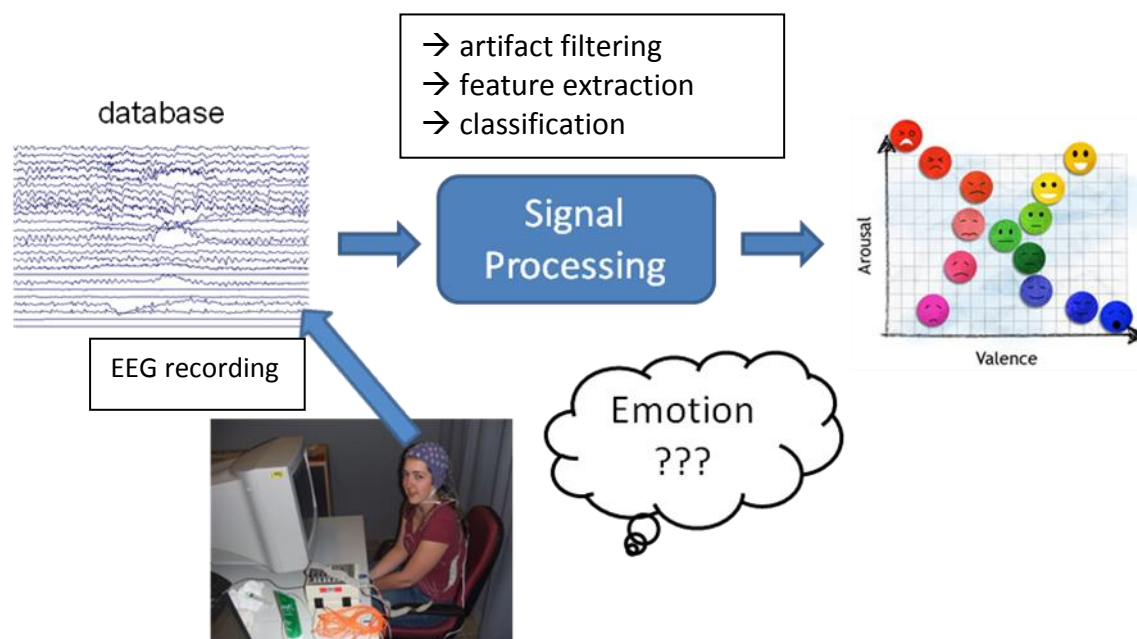


Figure 1: emotion recognition

## 2 EEG signals and emotions

Emotion recognition is one of the key steps towards emotional intelligence in advanced human – machine interactions. The research of emotion recognition consists of facial expressions, vocal, gesture, physiological signal recognition and so on. The classification in EEG signals is rather difficult, but other relatively easier efforts cannot detect the underlying emotion states.<sup>1</sup>

### EEG signals

Hans Berger made in 1924 the first recording of the electric field of the human brain. He gave this recording the name *electroencephalogram* (EEG). He described three different kinds of EEG signals. The spontaneous activity, the evoked potential, and the bioelectric events produced by single neurons. In this project the spontaneous activity is measured on the scalp with amplitude of about 100 $\mu$ V. The bandwidth of this signal goes from under 1Hz to about 50Hz, shown in the following figure.<sup>2</sup>

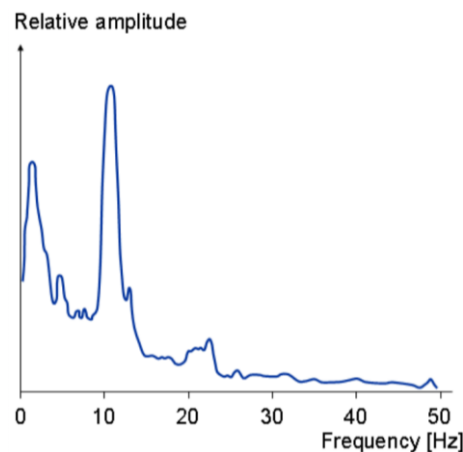


Figure 2 : Frequency spectrum of normal EEG

### The standardized 10 – 20 system

The standardized *10 – 20 system* is often used to record spontaneous EEG on the surface of the scalp. The size of the cranium of each person is different. Thus a relative system was defined, the standardized 10 – 20 system.

The distance between *naison* and *inion* is measured and defined as 100%. From the position of the *naison* in direction to the position of the *inion*, 6 steps are done to place electrodes:

<sup>1</sup> [1] M.Murugappan and Co, "EEG Feature Extraction for Classifying Emotions using FCM and FKM", p.1

<sup>2</sup> [11] <http://www.bem.fi/book/13/13.htm#03>

Beginning with a step of 10%, followed by 4 steps of 20% and ending up with a step of 10%. This movement is done in transversal and median planes, as you can see in the following figures.<sup>3</sup>

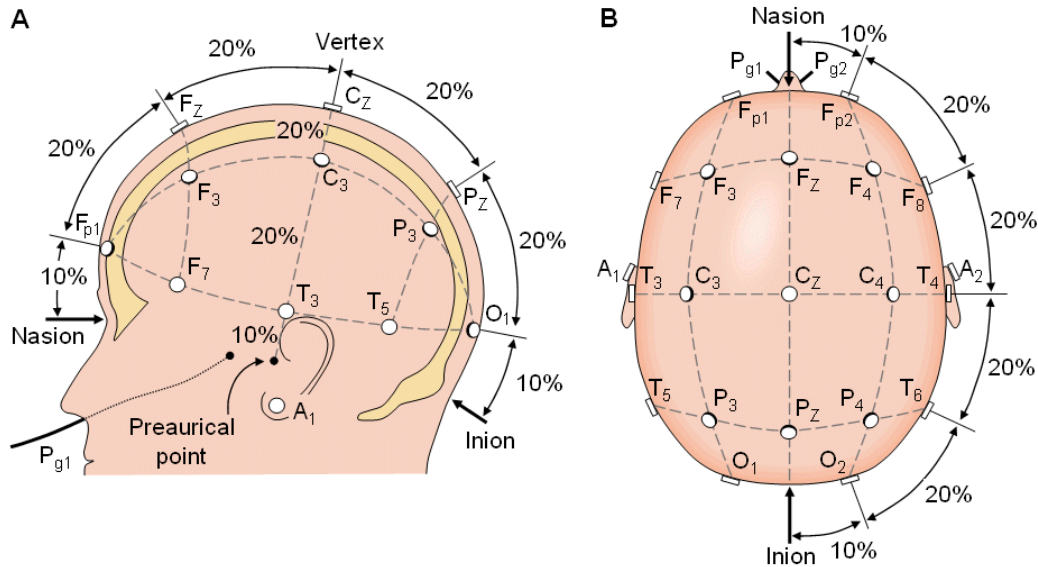


Figure 3 : the international 10 – 20 system seen from (A) left and (B) above the head. → A = Ear lobe, C = central, Pg = nasopharyngeal, P = parietal, F = frontal, Fp = frontal polar, O = occipital.

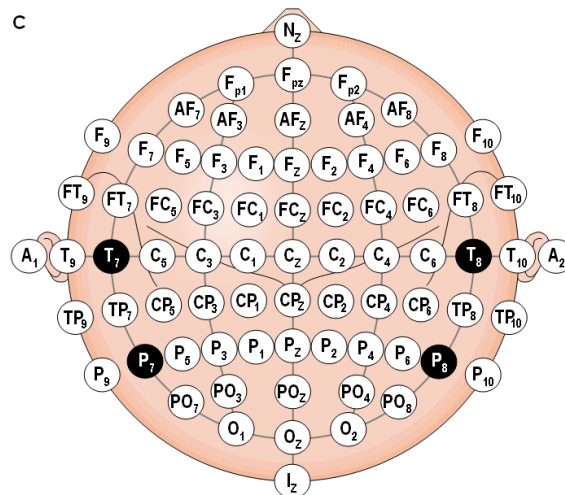


Figure 4 : (C) Location and nomenclature of the intermediate 10% electrodes, as standardized by the American Electroencephalographic Society (Redrawn from Sharbrough, 1991)

<sup>3</sup> [12] [http://www.life-science-lab.org/cms/tl\\_files/arbeitsgemeinschaften/neuropsychologie/eeg\\_ger.pdf](http://www.life-science-lab.org/cms/tl_files/arbeitsgemeinschaften/neuropsychologie/eeg_ger.pdf)

Bipolar or unipolar electrodes can be used in EEG measurements. With the bipolar electrodes the potential difference between a pair of electrodes is measured, with the unipolar electrodes the potential of each electrode is compared either to a neutral electrode or to the average of all electrodes.<sup>4</sup>

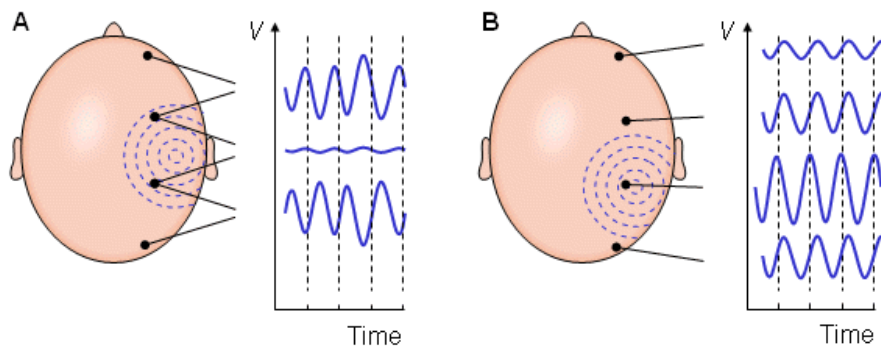
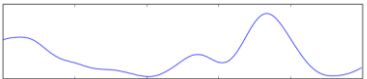
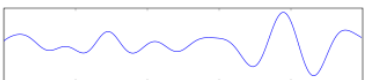
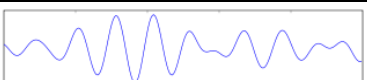
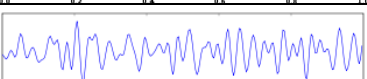
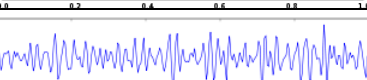


Figure 5 : (A) Bipolar and (B) unipolar measurements. Note that the waveform of the EEG depends on the measurement location.

## Frequency bands of interest in EEG signals

The frequency band of interest is shown in the following table:

TYPE	FREQUENCY (Hz)	EXAMPLES OF WAVEFORMS
Delta ( $\delta$ )	up to 4 Hz	
Theta ( $\theta$ )	4 – 8 Hz	
Alpha ( $\alpha$ )	8 – 12 Hz	
Beta ( $\beta$ )	12 – 30 Hz	
Gamma ( $\gamma$ )	30 – 100 Hz	

The delta frequency range is usually the slowest waves with the highest amplitude. It is typically seen in adults in slow wave sleep. The theta frequency range may be seen in

<sup>4</sup> [11] <http://www.bem.fi/book/13/13.htm#03>



drowsiness or arousal in adults, but normally this wave is seen in young children. The alpha frequency range is brought out by closing the eyes and by relaxation, called “posterior basic rhythm”. The beta frequency range is closely linked to motor behavior and is generally attenuated during active movements. And the gamma frequency range are thought to represent binding of different populations of neurons together (= to do two different things on the same time).

### Emotions and models

Emotion is an important aspect in the interaction and communication between people. Emotions are intuitively known to everybody, but it’s very hard to define them scientifically. To be able to measure and classify emotions, some models were developed. In this project the dimensional model is used. This model places emotions on a multidimensional scale. One dimension is the emotion valence, with positive and negative valence. The other axis is the dimension arousal, with negative and positive arousal. This model is used, because it is relatively simple and universal.

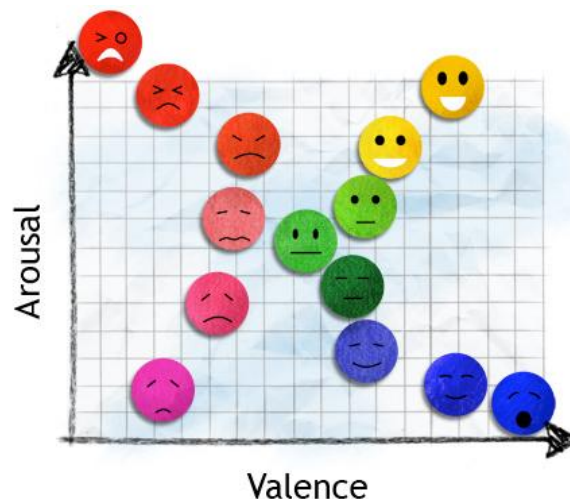


Figure 6 : dimensional model<sup>5</sup>

<sup>5</sup> [9] Robert Horlings, “Emotion recognition using brain activity”, Man-Machine Interaction Group, TU Delft, 27 March 2008

## 3 Different methods

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Overall, the main idea of all methods, which is to extract and classify information taken from EEG signals, follows the same steps. First preprocessing is done, then a method, like FFT, wavelet, etc. to extract features is chosen. And finally the information is classified by a selected classifier. Sometimes a feature reduction or normalization is done before the classification.

In the following paragraphs a short summary of some feature extraction and classifier methods are presented.

### 3.1 Preprocessing

To extracting features from EEG data and performing classification, we need to pre-process signals to remove noise. The preprocessing step depends on the kind of noise we have. Noise can originate from several sources: environment (mainly 50Hz), muscles activity, techniques to record the signal, etc.

The frequency band of interest is between 4Hz and 45Hz. Other frequencies are often filtered out and only the frequency band of interest is kept. Another popular preprocessing step is to subtract the mean of reference channels from each other channel.

### 3.2 Feature extraction

There are a lot of different methods for feature extraction. In the following paragraphs some of them are presented.

#### Common set of features

A relative simple and popular method is to take a common set of features<sup>6</sup> like the Mean, the Standard deviation, the skew ness, the Kurtosis, the Mean of the absolute values of the first difference of raw signals or the Mean of the absolute values of the first difference of normalized signal. This feature extraction is chosen in [5] and in [6].

A similar set of features in the time domain is computed for each bio – signal in [3]. The six feature values can be seen in the following figures.

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<sup>6</sup> [6] Z. Khalili, M.H. Moradi, Emotion Recognition System Using Brian and Peripheral Signals: Using Correlation Dimension to Improve the Results of EEG

$$\begin{aligned}
 \mu_X &= \frac{1}{T} \sum_{t=1}^T X(t) \\
 \sigma_X &= \sqrt{\frac{1}{T} \sum_{t=1}^T (X(t) - \mu_X)^2} \\
 \delta_X &= \frac{1}{T-1} \sum_{t=1}^{T-1} |X(t+1) - X(t)| \\
 \bar{\delta}_X &= \frac{1}{T-1} \sum_{t=1}^{T-1} |\bar{X}(t+1) - \bar{X}(t)| = \frac{\delta_X}{\sigma_X}, \\
 \gamma_X &= \frac{1}{T-2} \sum_{t=1}^{T-2} |X(t+2) - X(t)| \\
 \bar{\gamma}_X &= \frac{1}{T-2} \sum_{t=1}^{T-2} |\bar{X}(t+2) - \bar{X}(t)| = \frac{\gamma_X}{\sigma_X}
 \end{aligned}$$

Figure 7 : feature extraction in time domain

### Fourier Frequency Analysis

Two different methods are proposed in [2] and in [10]. In [2] a FFT (Fast Fourier Transform) is used for feature extraction. Only the frequency range from 5 to 40 Hz is kept, because all necessary information is in this frequency range. By averaging over adjacent frequency components, the dimensionality of the resulting feature vectors is downsized. In [10] a bandpass filtering in the frequency domain is applied. Only the alpha (8 – 12Hz) and the beta (12 – 30Hz) frequency are kept. The signal is transformed back into the time domain and the power is computed.

### Wavelet Transform

In [1] a wavelet transform is used for the feature extraction. A wavelet is a small oscillatory wave which has its energy concentrated in time. This method allows analyzing simultaneously in the time and frequency domain. It's a suitable tool for transient, non-stationary or time-varying signals. The non-stationary nature of EEG signals is to expand them in basis function created by expanding, contracting and shifting a single prototype function.

In [1] a Daubechies order 4 wavelet transform (db4) is used, because of their near optimal time frequency localization properties and also their waveforms are similar to the waveforms to be detected in the EEG signal. The extracted wavelet coefficients allow a compact representation showing the energy distribution of the EEG signal in time and frequency.

### Time and frequency domain

According to [2], different features from the time and frequency domains are extracted. Peak alpha frequency, which is the frequency with the maximum amplitude in the alpha power spectrum, was used. And also Alpha power and cross-correlation features were computed.

## 3.3 Classification

After a feature extraction a classifier is chosen to classify the extracted information. In the different papers is shown, that the choice of the classifier influence the result. In the following paragraphs some comparisons between classifiers are presented.

### Clustering

Clustering is a good method if the labels aren't known. With this method it's possible to find similar points. In [1] the Fuzzy – C Means clustering (FCM) and the Fuzzy – K Means clustering (FKM) are used. FKM works better for less feature values than for a high number of feature values. There was no difference with FCM for a higher or smaller number of feature values.

### Neural Network Models

Four popular neural network models were compared in [3]. The four models were: Multilayer Perceptron (MLP), Decision Ttree (DT), Bayes network and Support Vector Machine (SVM). The best result of these four methods was reached from the MLP.

A similar result as the SVM was achieved with a new learning model based on Relevance Vector Machines (RVM).

### Quadratic Discriminant Analysis (QDA) and Leave – One – Out (LOO)

In [6] a QDA is compared with a LOO. The LOO is a kind of a k – Nearest Neighborhood (kNN) classifier. In the result is show, that with the LOO they got a slightly better result than with a QDA classifier.

In [5] a Linear Discriminant Analysis (LDA) is compared with a kNN classifier. They showed, that the results with a kNN classifier are much better than with a LDA.

Overall, there are a lot of different classifiers. The choice of the classifier is also dependently of the feature values. If a training set is available, that means if the labels are known), a neural network model like the MLP can be a good choice. If the labels aren't known, other methods like FCM or FKM should be chosen. Also the number of available samples influences the choice. For a neural network model, as more samples are available for the training as better.

## 4 EEG database

The data for this project is collected from a database. The database contains three different modalities to record emotions. One modality is brain signals via fNIRS, the second modality is face video and the third modality is the scalp EEG signals. In this project we are only interested in the EEG signals. The database can be downloaded from the following siteweb:

<http://www.enterface.net/results/> (project 7, eNTERFACE'06).

### 4.1 Experimental protocol for EEG signals<sup>7</sup>

Subjects were seated in front of a computer screen and watching images in a randomly order. The images were chosen in a way they provoke emotions. In the study, data from 5 subjects (all male and right handed, with age ranging from 22 to 38) were recorded using the Biosemi Active 2 acquisition system with 64 EEG channels. The following ten frontal electrodes had to be removed: F5, F8, AF7, AF8, AFz, Fp1, Fp2, Fpz, F7, F6. That means only 54 channels are kept. All EEG signals were recorded at 1024 Hz sampling rate except the first session of participant 1 that was recorded at 256 Hz.

You can see the detailed protocol in the following figure.

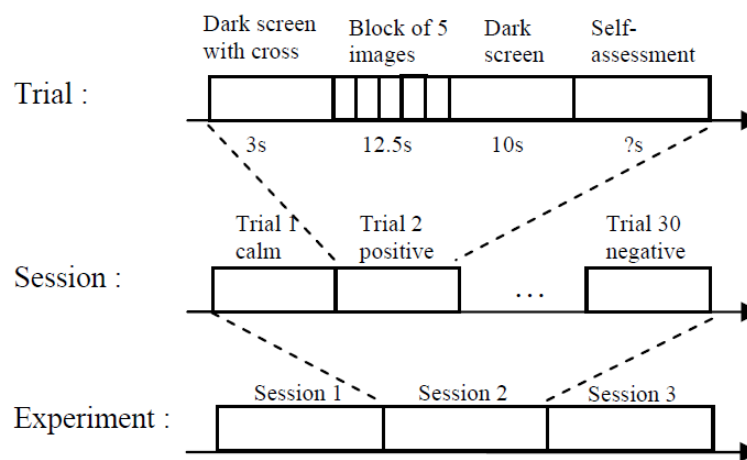


Figure 8 : Protocol description

The whole experiment for one subject has been divided in three parts (session 1 to session 3), because the tight placement of the EEG and fNIRS devices can cause some discomfort after a while. One session has duration of approximately 15 minutes and every session is placed on different days. Each session contains 30 trials. Each trial starts with a dark screen with a cross for 3 seconds to attract the user attention, followed by a block of 5 images. Each image is displayed on the screen for 2.5 seconds and is from the same class to insure stability of the

<sup>7</sup> [4] Arman Savran and Co, Emotion Detection in the Loop from Brain Signals and Facial Images, p.1,3,4

emotion over time. After again looking to a dark screen, the subjects are asked for a self-assessment of the images by giving a score between 1 and 5 for respectively valence and arousal components, because one can never be very sure whether a block elicits the expected emotion or not. The blocks of images have different classes and are displayed in random order to avoid participant habituation. Overall, for each subject we have 3 sessions times 30 image blocks times 5 images, gives us 450 images per subject.

## 4.2 Database collection<sup>8</sup>

### *EEG and peripheral data*

The EEG signals are stored in a BDF (Biosemi Data Format) format. In this project eeglab is used to open the .bdf and to export them to matlab.

There are two files: a BDF file with EEG and peripheral signals and MRK file with the index of samples for each trial. The numbers stored in this file are the number of samples for each start and each stop point of a trial. There are 62 numbers, the first and second as a test and the third is the start of the first trial.

The name of this two files are:

PARTA\_IAPS\_SESB\_EEG\_fNIRS\_DDMMAAAA.bdf  
PARTA\_IAPS\_SESB\_EEG\_fNIRS\_DDMMAAAA.bdf.mrk

A: participant number (1 to 5), B: session number (1 to 3) and DDMMAAAA is the date of recording

### *Common data*

In this section the files that are common are described:

IAPS\_Images\_EEG\_fNIRS.txt contains three columns, one per session, with the names of the IAPS pictures used in the study.

IAPS\_Eval\_Valence\_EEG\_fNIRS.txt and IAPS\_Eval\_Arousal\_EEG\_fNIRS.txt contains in three columns the valence or arousal value for each image.

IAPS\_Classes\_EEG\_fNIRS.txt list in three columns the associated classes we considered for each block of pictures. Labels can be "Calm", "Pos" or "Neg".

Part ASESb.log lists self-assessment of participants. As for the EEG files, A is the number of participant while B is the session number.

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<sup>8</sup> [4] Arman Savran and Co, Emotion Detection in the Loop from Brain Signals and Facial Images, p.5-6

## 5 Implementation and validating

The algorithm in this project is divided in three main parts. First, there is the “Preprocessing” part. In this part the signal is windowed and some channels were selected. In a second part a feature extraction is computed. And in the last part the extracted features were classified by a classifier.

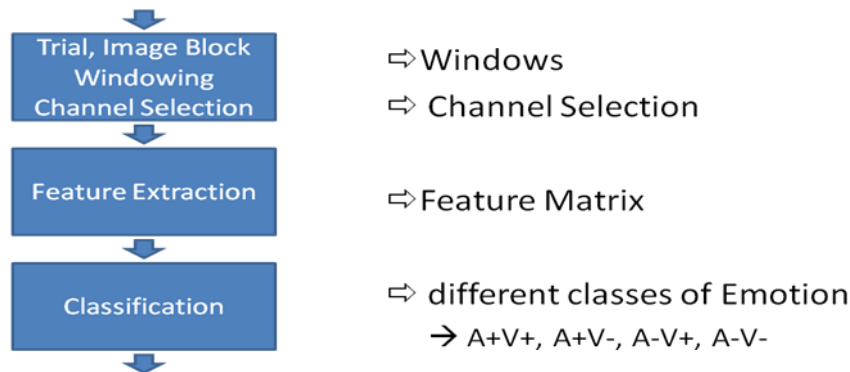


Figure 9 : Algorithm of the project

### 5.1 Windowing and channel selection

#### Windowing

The sequence of interest in this project is the image block in each trial. The image block has duration of 12.5 seconds and is composed of 5 images with a duration of 2.5 seconds. The durations of the trials are very different. To find the start and end point of a trial the index number is multiplied by the sample size. As written in paragraph 4.5 *Database collection*, the start and end point of a trial is stored in a .mrk file as a index number of samples. The sample frequency is 1024Hz, thus the length of a sample is 1/1024 second. Once the start of a trial has been found, the start of an image block can easily be calculated by adding 3 seconds.

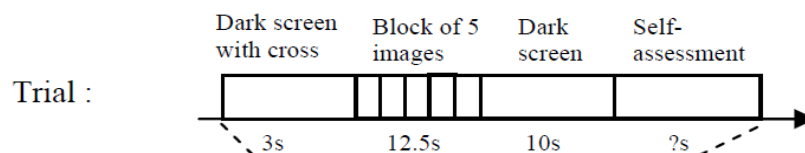


Figure 10 : a Trial

The image block is windowed with a window of 0.5 seconds. To have good information on the boards of a window, an overlapped windowing was done. Finally that gives 9 windows per image, thus 45 windows per image block, thus 1350 windows per session.

### Channel selection

To reduce the size of the data 16 channels were collected arbitrary and 2 channels were selected as reference channels. In the following figure you can see the map of the placement of the 64 electrodes according to the “10 – 20 electrode placement system”. A channel means an electrode. T7 and T8 (green) were selected as reference channels. The channels AF3, AF4, F3, F4, FCz, C3, Cz, C4, CPz, P3, Pz, P4, POz, O1, Oz and O2 (red) were selected for the feature extraction.

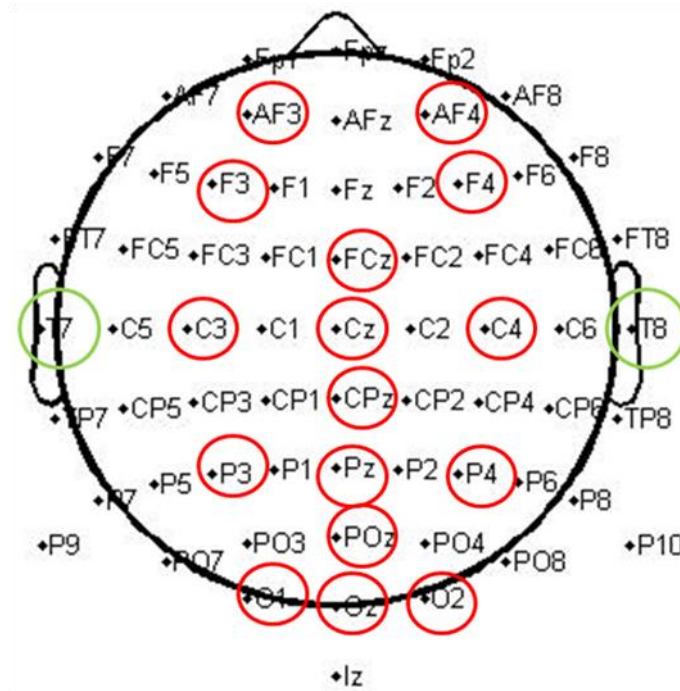


Figure 11 : channel selection

## 5.2 Feature extraction

For the feature extraction the discrete wavelet transform (DWT) is chosen. In this project a Daubechies order 6 wavelet (db6) is used. The extracted wavelet coefficients allow a compact representation showing the energy distribution of the EEG signal in time and frequency domain.

Before the wavelet transform is computed, the mean of the reference channels T7 & T8 was subtracted from each channel.

The sampling frequency is 1024Hz. Decompositions for level 8 are computed and level decompositions from level 4 to 8 are kept. As you can see in the following figure, all levels of interest in EEG signals are covered with db4 to db8:



Decomposition levels	Frequency Bandwidth (Hz)	corresponding frequency band of interest in EEG
D8	2 – 4Hz	δ (Delta)
D7	4 – 8 Hz	θ (Theta)
D6	8 – 16 Hz	α (Alpha), β (Beta)
D5	16 – 32 Hz	β (Beta)
D4	32 – 64 Hz	γ (Gama)

Figure 12 : table of the frequency bands

For each window and each channel the 5 decompositions levels (d8 to d4) are kept. In the following figure, you see an example of window 10 and channel O2. For one window, there are 16 channels and 5 decompositions levels. This means, finally 16 times 5 (= 80) decomposition levels are computed.

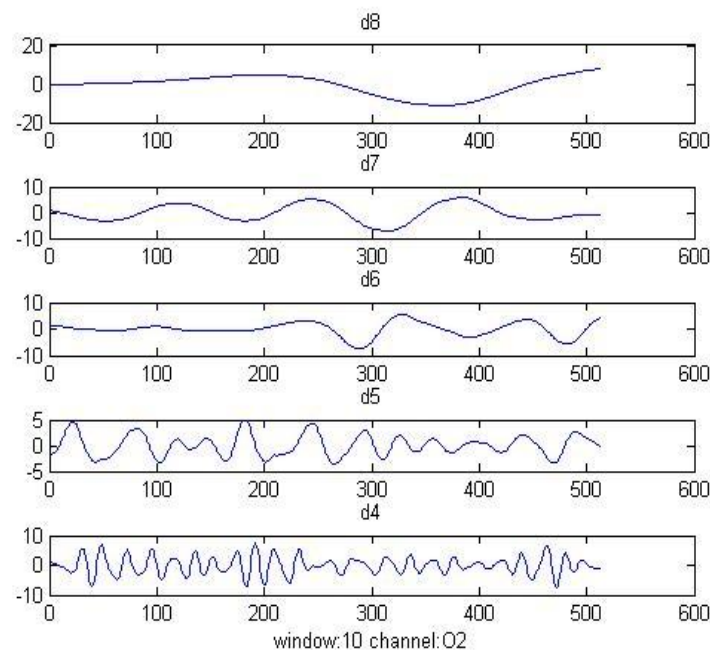


Figure 13 : decompsition leves (d8 to d4)

With the Parseval Formula the Energy of each decomposition level are calculated. That gives us 80 (16 channel \* 5 decomposition levels) values for each window.

$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \int_{-\infty}^{\infty} |X(f)|^2 df$$

Figure 14 : Parseval Formula

If for each window of a session the energy is calculated, a feature matrix of size 1350 x 80 is obtained.



Figure 15 : Feature Extraction

The feature matrix is normalized with the following formula. The mean is subtracted from each value. This difference is divided to the standard deviation.

$$\frac{X - \mu}{\sigma}$$

Figure 16 : Normalization

### 5.3 Classification

Before the classification method is described, the classes are presented.

#### Different classes

In the figure bellow you can see 4 classes. The green field is positive valence and positive arousal, the red field is positive arousal and negative valence, the yellow field is negative arousal and negative valence and the blue field is negative arousal and positive valence.

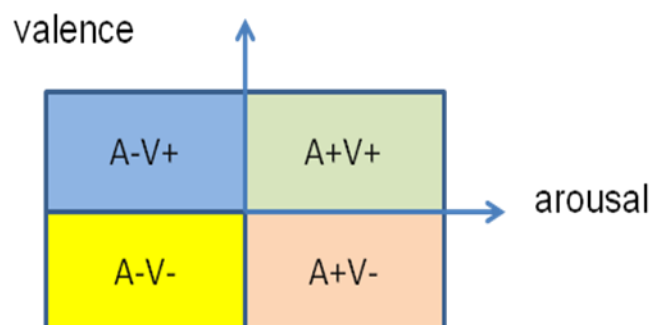


Figure 17 : classification map

To simplify, only two classes are classified at once. The two classes positive arousal (A+) and negative arousal (A-) were classified and once positive valence (V+) and negative (V-) were classified.

Then, calm versus positive and calm versus negative and positive versus negative were classified. The definitions of calm, positive and negative are in the following table.

If the range of arousal and valence is from -4 to 4, the definition of calm, positive and negative is:

<b>calm:</b> $\overline{arousal} < -1; -1 < \overline{valence} < 1$
<b>positive exciting:</b> $\overline{valence} > 1.8; \text{Var}(\text{valence}) < 2; \overline{arousal} > 0$
<b>negative exciting:</b> $\overline{valence} < -2; \overline{arousal} > 0$

### Classification

All labels are known and a big number of samples are available. Thus a Multi Layer Perceptron (Neural Network) classifier is used as you can see in the following figure. All three feature matrix of the three sessions of one subject are put together. A big feature matrix of size 80 x 4050 is obtained. This big matrix of 4050 samples is used as an input. 60% from these 4050 samples (2430 samples) are used to train the Multi Layer Perceptron. 5% from the 4050 samples (203 samples) are used for validation to prevent the effect of over testing. Finally 35% of the samples (1417 samples) are used for classification (as a test).

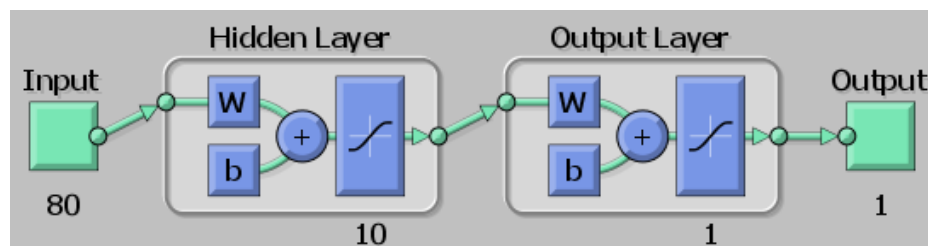


Figure 18 : Multi Layer Perceptron / Neural Network

### 5.4 Results

In the following figure the final result is presented. The first bar shows the correctly classification of the two classes positive and negative arousal. 35% of the samples (= 1417 samples) are tried to correctly classified. The 66% in the figure means that in average 66% of the 1417 samples are correctly classified in class arousal positive or arousal negative.

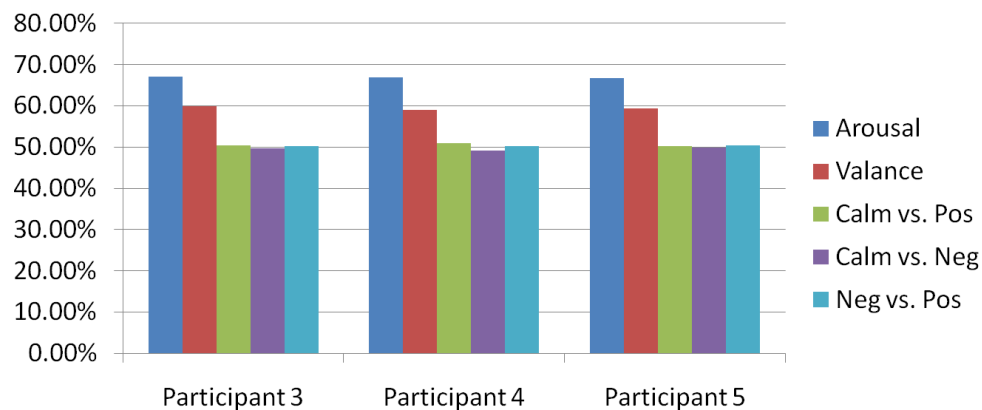


Figure 19 : Results (% of a correct classification)

Overall, for the classes arousal and valence between 60% and 70% are correctly classified. It seems that there is a difference in the EEG signal between positive arousal and negative arousal and between positive valence and negative valence. But the correct classification between calm and positive, calm and negative, and negative and positive is only around 50%. For a classification of two classes it means, that the classification is like a random classification.

Other wavelets are used for the discrete wavelet transform to improve the results. Once the wavelet coiflets order 4 ('coif4') is used and once the wavelet symlets order 6 ('sym6') is used. The results are the same as with the wavelet daubechies order 6 ('db6').

## 6 Comparing the results

In [6] the same database was used to recognize emotions. As features extraction a common set of features, like the mean, the standard deviation, the skew ness, the kurtosis, the mean of the absolute values of the first difference of raw signals and the mean of the absolute values of the first difference of normalized signal were extracted. Then the Genetic Algorithm (GA) was applied to select features. With the QAD (Quadratic Discriminante Analyses) classifier and the LOO (Leave – One – Out) classifier similar results comparing to this project were obtained, as you can see in the following figure.

DiagQuadratic	EEG (one participant)
Half: train, half: test	63.33 %
LOO	66.66 %

In [5] the same database was used to recognize emotions. The same common feature extraction as in [6] were chosen and also the GA was applied to select features. Comparing to [6] a LDA (Linear Discriminant Analysis) classifier and the k – Nearest Neighborhood (kNN) classifier was chosen. In the following figures is shown, that for 2 classes a slightly worse result is obtain than the previous result. For three classes the result is the worst.

### 3 classes

classifier	EEG
LDA	40 %
KNN	51 %

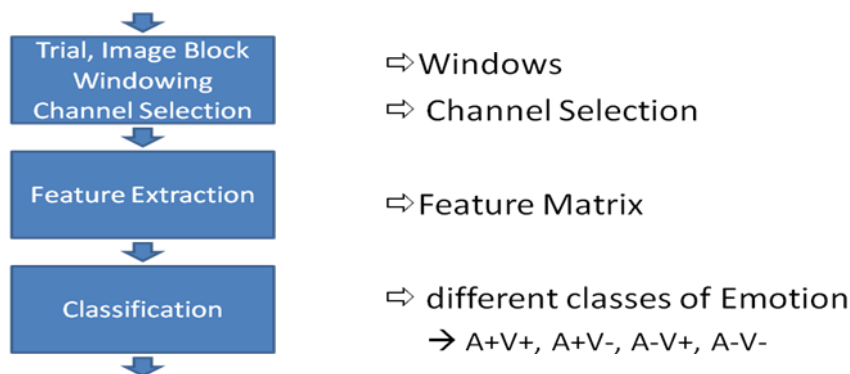
### 2 classes

classifier	EEG
LDA	50 %
KNN	65 %

## 7 How to use the database and the scripts?

My algorithm is structured as shown in the following figure. You have to do 5 main steps:

1. **Download the database and eeglab.**
2. **First part of the algorithm: Trial, Image Block, Windowing, etc.**
3. **A manual intermediate step.**
4. **Second part of the algorithm: Feature Extraction**
5. **Third part of the algorithm: Classification**



### 1. Download database and eeglab

Before you can run the code, you have to **download the database and eeglab**. (→ for the classification part you should have at least a matlab version 7.7)

**The database** can be found on the following website: <http://www.enterface.net/results/>

→ Download the project 7 database from the eNTERFACE'06 workshop. On the same page you can also find a project description.

You can find **the eeglab** on this website: <http://sccn.ucsd.edu/eeglab/eeglabtut.html> → on this website you can also find a link to an eeglab wiki and a link to a tutorial.

If you want to run the matlab code without changing the paths, you should have the same structure of folders as you can see in the following figure.

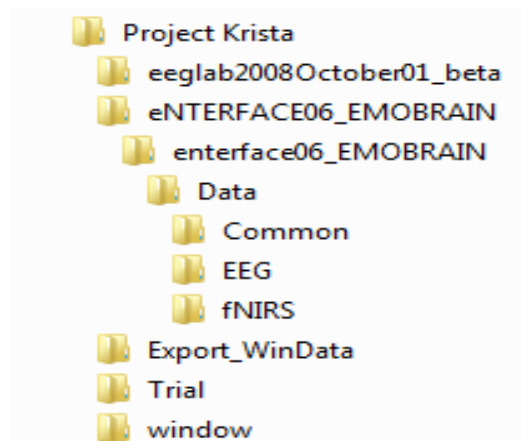


Figure 20 : structure of folders

You can find the EEG signals in the folder EEG. They are stored as .bdf files. That's why eeglab is used. In the same folder you can find the triggers (bdf.mrk files). Replace them with the trigger files given on the cd. All matlab files are stored in folder project krista. In folder "Common" you can find the original files with the labels. (useful for classification)

## 2. First part of the algorithm: Trial, Image Block, Windowing, etc.

The goal of this part is to find the sequence of interest (Trials and Image Blocks), to select the channels and to windowing the Image Block.

You have to run the **EXE.m** file, but you should know, that it's very time consuming, because the script takes lot of functions from the eeglab. → You can write a faster code by combining the four functions of the EXE.m file. Then, eeglab hasn't to load the signals for each function again, but then you can't run the functions separately.

You can change the **input values** Part, SES and dat. Part is the number of the participant (from 1 to 5), SES is the number of the session (from 1 to 3) and dat is the date on which the data was recorded. (You can find the date in the name of the original eeg signal in folder EEG)

The EXE.m file contains the following functions:

□ *load\_mark\_files.m*

→ The function loads the triggers for each session. A trigger is an index of samples and is set at the end and beginning of each trial.

□ *find\_trials.m*

→ The function cut the eeg signal in trials and store them in the folder "Trial". The name is PartX\_SESY\_TrialZ. (X: Participant 1 to 5, Y: Session 1 to 3, Z: Trial 1 to 30)

□ *image\_block.m*

→ The function selects only the sequence of the image block. An image block is composed of 5 images all with duration 2.5 seconds (= 12.5s per image block). At the same time 18 channels are selected (2 as reference channels). Each image block is windowed with an overlapped window of size 0.5s. Finally 49 windows are got from each image block, whereas window 10, 20, 30, 40 aren't used, because they are between two images. Each image block is stored in the folder "Trial" with the name PartX\_SESY\_ImageBlockZ (X: Participant 1 to 5, Y: Session 1 to 3, Z: ImageBlock 1 to 30). Each window is stored in the folder "window" with the name PartX\_SESY\_ImageBlockZ\_windowxx (xx: window from 1 to 49).

□ *Export\_WinData.m*

→ The function exports the window data from eeglab. The exported data are stored in folder "Export\_WinData" as .txt files.

**IMPORTANT:** You can find the already exported data in subfolders of Export\_WinData. So you can skip the first part of the algorithm and directly go to the second part of the algorithm (feature extraction).

### 3. A manual intermediate step.

Matlab has a problem to load the exported data. Before you can move on to the next step (feature extraction) you have to change the .txt files. You have to replace all tab (" ") by a comma (","),. For example the program Notepad++ is very useful for this step.

### 4. Second part of the algorithm: Feature Extraction

The goal of this part is to extract feature values with a wavelet transform. You will have a feature matrix of size 80 x 1350 for each session at the end of this step.

Open the **FV\_wavelet.m** file and run the code. You can choose the session (SES) of a participant (Part) as input value. You have to adapt the name manually.

The FV\_wavelet.m file contains the following functions:

□ *load\_Export\_WinData.m*

→ The function loads the exported data from the folder "Export\_WinData".



□ *feature\_vectore.m*

→ The function extracts a feature vector for each window. A wavelet transform is used and the 5 last decomposition levels are kept. For each channel and decomposition level the energy is calculated with the Parseval formula.

→ At the end you get a feature matrix with size 80 x 1350 for one session of a participant. To go to the next step you should have at least the feature matrixes of all three session of a participant.

### 5. Third part of the algorithm: Classification

The goal of this step is to classify the extracted features. There are two possibilities:

- Classify negative arousal vs. positive arousal or negative valence vs. positive valence.  
→ open the file Classification.m
- Classify clam vs. positive, calm vs. negative or negative vs. positive. → open the file class\_class.m

The neural network toolbox is popped – up. Play with the toolbox to get good results. =)

**Remark:** In data3, data4 and data5 feature vectors from participant3, participant4 and participant5 with the corresponding labels are stored. → Useful if you want skip the feature extraction step.

Good luck =)

### SUMMARY

1. **Download eeglab and the database.**
  - Replace the trigger files.
  - Check the correct order of the folders.
2. **Run EXE.m for windowing, etc.**
  - You can skip this part by taken the data from the CD. (find them in subfolders of Export\_WinData)
3. **Replace the TABs with COMMAs in all files of folder Export\_WinData**
4. **Run FV\_wavelet.m for extracting features.**
5. **Classification with the nprtool (neural network toolbox)**
  - Run Classification.m for classes arousal and valence
  - Run class\_class.m for classes positive, calm and negative

## 8 Conclusion and Acknowledgements

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Emotion recognition from EEG signals is a challenging task and there are a lot of problems to overcome. I saw that probably the used database isn't very good for the EEG signal part, because I didn't got good results and I found other people, which had similar bad results than me. So, it is difficult to evaluate my algorithm.

Overall there are still many parameters they could be improved. In this project the channel were chosen arbitrary. Perhaps there is another better method to choose the channels as for example the Genetic Algorithm (GA). A lot of different methods to extract features are presented in this project. By implementing other methods it could be tried to get better results. Another important point is the choice of the classifier. We saw, that the result could be very different with another classifier.

Another challenge of this project was to work with a big database. The challenge was to first really understand the database and then to work with a big size of data. To run a simple matlab code was already time consuming.

Overall it was a very interesting project and I've learned a lot. I thanks my assistant Ashkan Yazdani und my Professor Dr. Tourady Ebrahimi for their encouragement and assistance.

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[15] title image: [www.brainfitnessinc.com/images/Braingears.jpg](http://www.brainfitnessinc.com/images/Braingears.jpg)