Faculty of Engineering and Architecture
Departement ELIS
2015–2016

Recognize Emotion in the brain using EEG Data

by

Andreas DE LILLE

Promotors: Prof. J. DAMBRE
Dr. Ir. P. VAN MIERLO
Assistent: Ir. T. VERHOEVEN

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Nomenclature

BCI Brain Computer Interface

DASM Differential Asymmetry

DCAU Differential Caudality

DEAP Dataset for Emotion Analysis using Physiological Signals

EEG Electroencephalography

GSR Galvanic Skin Response

MEG magnetoencephalography

OCR Optical Character Recognition

oob out of bag

PSD Power Spectral Density

RASM Rational Asymmetry

RCAU Rational Caudality

RF Random Forests

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1

Introduction

This chapter describes the context of the thesis, starting with brain computer interfaces(BCI), before defining some BCI basics. After that, the P300 speller and P300 paradigm are introduced. Before the need for an emotionally aware P300 speller is justified, the basic process of emotion in the brain is explained.

1.1 Brain computer interfaces

A Brain Computer Interface (BCI), creates a direct neural link from the brain to the computer[1], that tries to recognize patterns and based on the extracted information, performs actions. A BCI removes to need for physical actions, i.e. typing or moving a mouse, for the transfer of information. The neural link provided by the BCI is made of two important components. The first component is the extraction component, which extract brain signals from the brain. The second component is the computer that interprets signals and performs actions based on the outcome.

1.1.1 Electroencephalography (EEG)

Different technologies exist to analyze the brain, the most convenient method is via Electroencephalography (EEG), since it is a non-invasive method. Non-invasive methods, in contrast to invasive methods require no surgery; they simply measure electrical activity using electrodes placed on the scalp.

The electrical activity in a brain is caused when an incoming signal arrives in a neuron. This triggers some sodium ions to move inside the cell, which in turn, causes a voltage rise[2]. When this increase in voltage reaches a threshold, an action potential is triggered in the form of a wave of electrical discharge that travels to neighboring neurons. When this reaction occurs simultaneously in a lot of neurons, the change in electrical potential becomes significantly, making it visible to the EEG surface electrodes. EEG can thus only capture synchronized activity of many, many neurons.

Signals originating from the cortex, close to the skull, are most visible, while signals originating deeper in the brain cannot be observed directly. Even for signals originating close to the cortex, EEG is far from precise as the bone between the the cortex and electrodes distorts the signal.

Additionally other artifacts like eye and muscle movement add a lot a noise to the signal, noise removal techniques are therefor advised. Even though the noise is persistent and EEG data has very low spatial resolution, it still can provide significant insight into the electrical activity of the cortex while offering excellent temporal resolution[3].

Note that EEG records electrical activity, other methods like magnetoencephalography (MEG) measure brain activity using magnetic fields. Since MEG is more prone to noise from external magnetic signals, i.e. the earth's magnetic field and electromagnetic communication, a magnetic shielded room is required, making this method very expensive and not mobile.

EEG uses electrodes which are placed on the scalp to measure the electrical activity. To ensure that experiments are replicable, standards for locations of electrodes have been developed. One of these systems is the 10/20 system, an internationally recognized methods to describe location of scalp electrodes[4]. The numbers 10 and 20 refer to the distances between the electrodes, which are either 10% or 20% of the total front-back or left-right distance of the skull. Each site is identified with a letter that determines the lobe and hemisphere location.

- **F:** Frontal
- **T:** Temporal
- **C:** Central
- **P:** Parietal
- **O:** Occipital

Note that no central lobe exists; the C letter is only used for identification purposes. The letter z indicates that the electrode is placed on the central line. Even numbers are use for the right hemisphere, while odd numbers are used for the left hemisphere. A picture of a 23 channel 10/20 system is added below for clarification. Even though some experiment setups may use a different set of channels than shown in figure 1.1, they all follow the same naming convention.

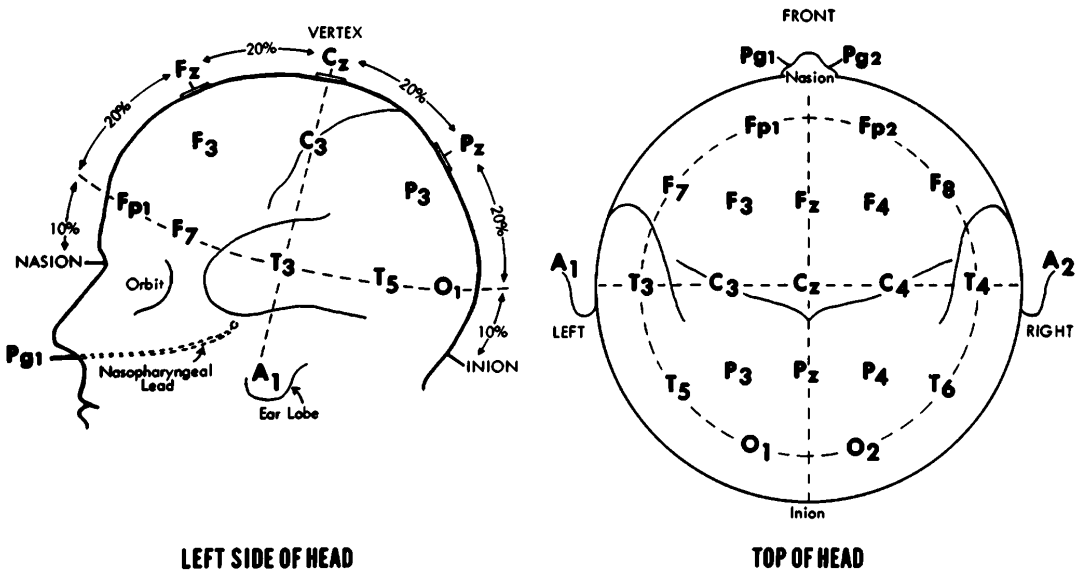

Figure 1.1: The electrode placement of a 23 channel system[5].

Two different types of EEG channels exist, monopolar and dipolar. A monopolar channel records the potential difference of a signal, compared to a neutral electrode, usually connected to an ear lobe of mastoid. A bipolar channel is obtained by subtracting two monopolar EEG signals, which improves SNR by removing shared artifacts[6].

In the frequency domain, brain waves are usually split up into different bands[7, 8], each band has a different medical interpretation. These wavebands are:

1. **Alpha:** 8-13Hz, indicate how relaxed and/or inactive the brain is.
2. **Beta:** 13-30HZ, indicate a more active and focused state of mind.
3. **Gamma:** 30-50Hz, relate to simultaneous processing of information from different brain areas.
4. **Delta:** 0-4hz, these waves are generated during dreamless sleep and meditation.
5. **theta:** 4-8Hz, occur during dreaming.

Most muscle and eye artifacts have a frequency around 1.2Hz. Artificats caused by nearby power lines, have a frequency around 50Hz[2]. To remove most of this noise, a bandpass filter is usually applied to filter out frequencies below 4Hz and above 40-45Hz.

1.2 Emotion recognition

Psychology makes a clear distinction between physiological behavior and the conscious experience of an emotion, called expression[2]. The expression consists of many parts, including the facial expression, body language and voice concern. Unlike expression, the physiological aspect of an emotion, e.g. heart rate, skin conductance and pupil dilation, is much harder to control. To really know one's emotions, it seems, one has to research the physiological aspect of the emotion. One possibility for this is analysis of brain activity via Electroencephalography[9], which is the main method for this thesis.

1.2.1 Emotion in the brain

Before emotions can be recognized, a classification model is needed. A common model to classify emotions is the bipolar arousal-valence model[2, 10], that places emotions in a two dimensional space. The main advantage of using a multidimensional model, is that all emotions are modelled in its space, even when no particular discrete label can be used to define the current feeling. Figure 1.2 shows the mapping of different emotions for this model.

Even though arousal and valence describe emotion quite well, a third dimension can also be added. The new model then has three dimensions: arousal, valence and dominance. Arousal indicates how active a person is and ranges from inactive, bored to active, excited. The valence indicates if the emotion is perceived as positive or negative. The third dimension, the dominance, indicates how strong the emotional feeling was and ranges from a weak feeling to an empowered, overwhelming feeling. The dominance component can aid to filter out samples of strong feelings, since feelings with low dominance are less likely to show significant effects.

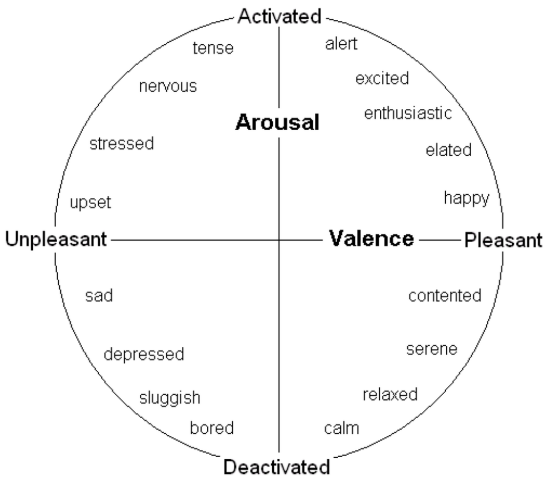

Figure 1.2: The arousal - valence model maps emotions in a two dimensional plane.

1.2.2 Features

The next step is defining relevant physiological features for emotion recognition, two categories of features are observed: EEG features and non-EEG features. The EEG features are features extracted from the electroencephalography measurements from the subject's scalp. This section will go through the used EEG features in this thesis.

The power spectral density (PSD) of a signal gives the distribution of the signal's energy in the frequency domain. By calculating the spectral density for different waveband of the signal, one can determine how much alpha, beta, ... power is in the signal.

Differential entropy is defined as follows [11]

$$-\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} exp(\frac{(x-\mu)^2}{2\sigma^2}) log(\frac{1}{\sqrt{2\pi\sigma^2}}) exp(\frac{(x-\mu)^2}{2\sigma^2}) dx$$

According to [12], the differential entropy of a certain band is equivalent to the logarithmic power spectral density for a fixed length EEG sequence, which simplifies the calculations significantly.

The most known feature for valence recognition is the frontal asymmetry of the alpha power[3]. The right hemisphere is generally speaking, more active during negative emotion than the left hemisphere which is in turn more active during positive emotions[10, 9, 11]. The asymmetry can be calculated in different ways, one of them is the differential asymmetry (DASM) , where the left alpha power is subtracted from the right alpha power.

$$DASM = DE_{left} - DE_{right}$$

Another way to measure the asymmetry if by division. The Rational Asymmetry (RASM) does exactly this and is given by:

$$RASM = \frac{DE_{left}}{DE_{right}}$$

With DE_{left} and DE_{right} being the left and right differential entropy respectively.

Another reported feature in literature is the caudality, or the asymmetry in fronto-posterior direction[13]. This can again be calculated in two ways. The first method is the differential Caudality (DCAU) is defined as:

$$DCAU = DE_{front} - DE_{post}$$

Another way to determine the Caudality is the Rational Caudality (RCAU) , which is defined as:

$$RCAU = \frac{DE_{front}}{DE_{post}}$$

With DE_{front} and DE_{post} being the frontal and posterior power respectively.

One way to determine the arousal is by looking at the different wavebands. Each waveband has their own medical interpretation, see 1.1.1. More alpha power corresponds to a more relaxed brain, while more beta power corresponds to a more active brain. The alpha / beta ratio therefore seems a good indicator for the arousal state of a person.

The aforementioned EEG features are just one class of physiological features. The DEAP dataset contains several physiological measurements, listed below [14]. For each of these measurements the average and the standard deviation is calculated.

The Galvanic Skin Response uses two electrodes on the middle and index finger of the subjects left hand to measure the skin resistance. It has been reported that the mean value of the GSR is related to the level of arousal[15, 14].

The respiration belt, indices the user's respiration rate. Slow respiration is linked to relaxation (low arousal), while fast and irregular respiration patterns corresponds to anger or fear, both emotions with low valence and high arousal[14].

A plethysmograph is a measurement of the volume of blood in the subject's left thumb. This can be interpreted as the the blood pressure. Blood pressure offers valuable insight into the emotional state of a person as it correlated with emotion; stress is known to increase blood pressure[14].

The heart rate is not explicitly in the DEAP dataset, but can be extracted from the plethysmograph, by looking at local minima and maxima[14]. This is clearly visible when looking at the plethysmograph's output, shown in Figure 1.3.

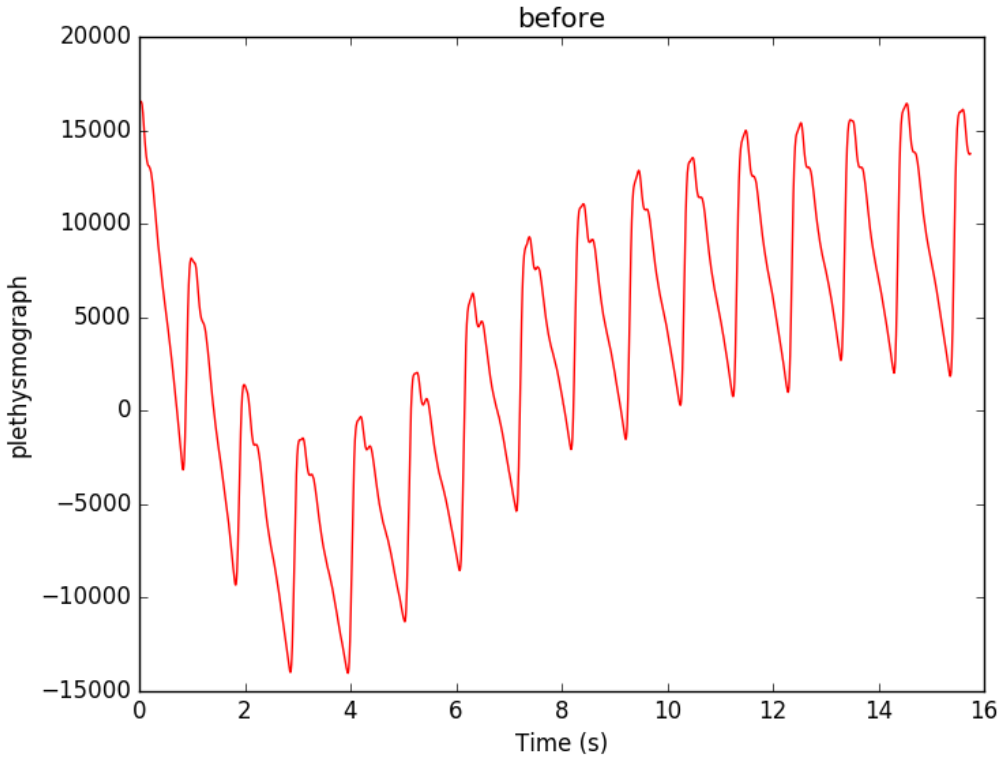

Figure 1.3: The plethysmograph before smoothing.

The heart rate extraction is done in two steps. First the plethysmograph signal is smoothed using a butter filter to avoid noise being selected as local optima. In the second stage the local optima are located, which is shown in Figure 1.4

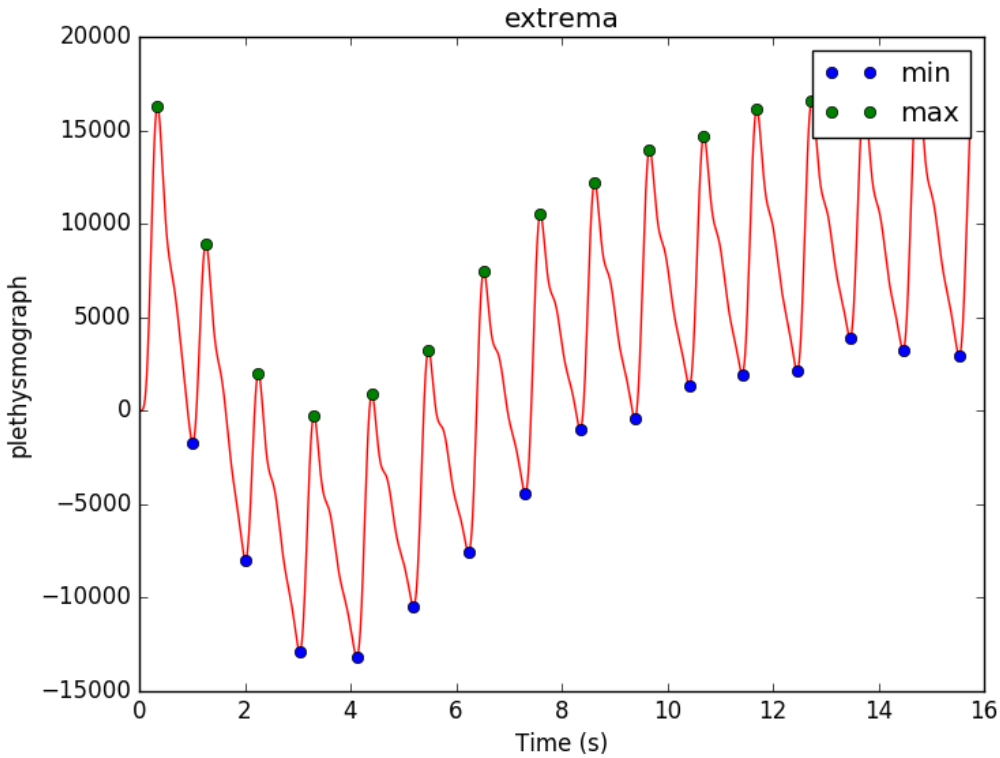

Figure 1.4: The local optima in the plethysmograph.

These optima correspond to a heart beat, therefore the time between two consecutive local minima or maxima corresponds to the time between two heart beats, known as the interbeat interval. Getting the average heart rate from the interbeat interval is straight forward.

The last physiological feature is the skin temperature of the subject.

1.3 Machine learning

The next important topic that needs to be covered is machine learning. Machine learning is the missing link between the features and the emotion recognition. As machine learning is a very broad domain, the discussion will be limited to the application of machine learning and machine learning techniques as this is the most relevant part for this thesis. One possible definition for Machine learning is: "the science of getting computers to act without being explicitly programmed". To do so, machine learning uses pattern recognition to find patterns or structure in the data. A simple example of machine learning is the Optical Character Recognition (OCR), where a computer recognises characters in pictures.

Let's get a look at the following example, to further explain how machine learning works. Suppose one has a price list of houses that are for sale combined with their total area. Logic sense dictates us that a bigger house will have a higher asking price than a smaller house. Therefore the asking price of a house is correlated to the asking price. Suppose you want to predict how much a certain home is worth, based on their area. This is possible with machine learning,

first you need to train your machine learning algorithm with a list of asking prices and the corresponding area of the house. This should give you a coefficient, lets say you pay 1000 euro for each square meter. Once this is done you can predict prices of new houses based on the corresponding area.

This will give some reasonable results, but the algorithm will probably have some flaws. This is due to the fact that the area of the house is only one feature that determines the price, there are many other that we haven't taken into consideration. Looking with more detail at the data, i.e. adding additional features will thus improve the performance of our algorithm. For example, a house with 5 bedrooms is more expensive than a house with only 3 bedrooms.

Machine learning algorithms are responsible for finding the relation between features and the predicted value. There exist many machine learning algorithms, one way to group these algorithms, is to look at their produced output. In the asking price examples above, the output is a price, which is a continuous value. The OCR example from above, where characters are recognized in a picture is a classification problem, as there is only a limited set of characters.

Another way to group the algorithms is based on their training data. In the asking price examples above one gets labelled results; the asking price is given for each area, this is referred to as supervised machine learning. The other possibility is unsupervised machine learning, which often results in finding groups of similar data points (clustering), without knowing the actual labels. Note that the combination of supervised and unsupervised data, also known as semi supervised learning, is also possible. Suppose you have a dataset with 5000 webpages and you want to categorise them in 10 distinct categories, e.g. science, nature, cooking, ... , but you only have the labels for 100 of the 5000 pages. Then you could first cluster the pages in similar groups using unsupervised learning. As soon as a group contains a labelled page, you can label all the pages in the group, since clustering returns groups of similar examples. Semi supervised learning has the advantage that one can also use unlabelled data. Unlabelled data is often easy and cheaper to obtain, unlike labelled data which is usually quite rare; if you had a fast and easy way to label the data then you wouldn't be needing machine learning.

In this thesis machine learning is used to find patterns in the aforementioned features that indicate the user's emotional state.

1.3.1 Over and underfitting / high bias and high variance

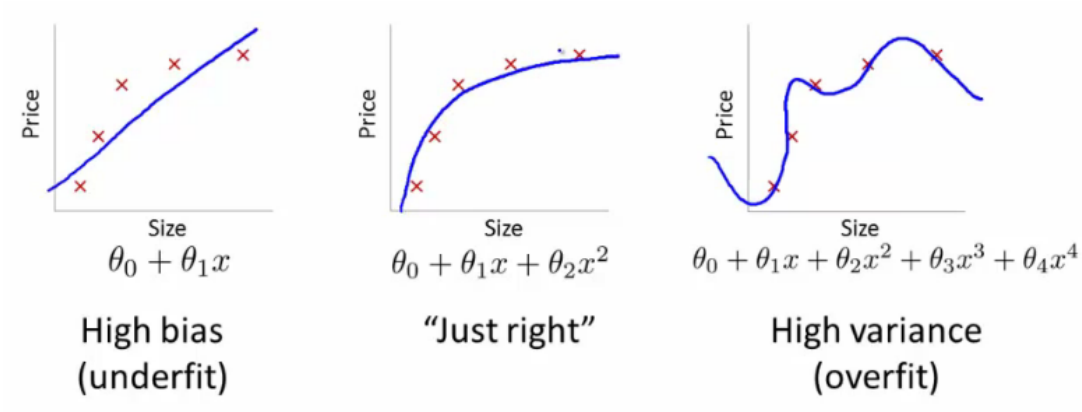

Figure 1.5: Overfitting versus underfitting[16].

Suppose the example in Figure 1.5, where one tries to find a good function to fit the given data points. Looking at the three proposed functions, one can easily see that the middle figure is the most likely generator function of the red points.

The figure on the left corresponds to an underfit, where the proposed function is not able to capture sufficient detail of the points. The function is not complex enough to approach the generator function, which is known as high bias. A high bias problem has a high training error, as the function is not able to fit the points correctly, this is visible in Figure 1.6

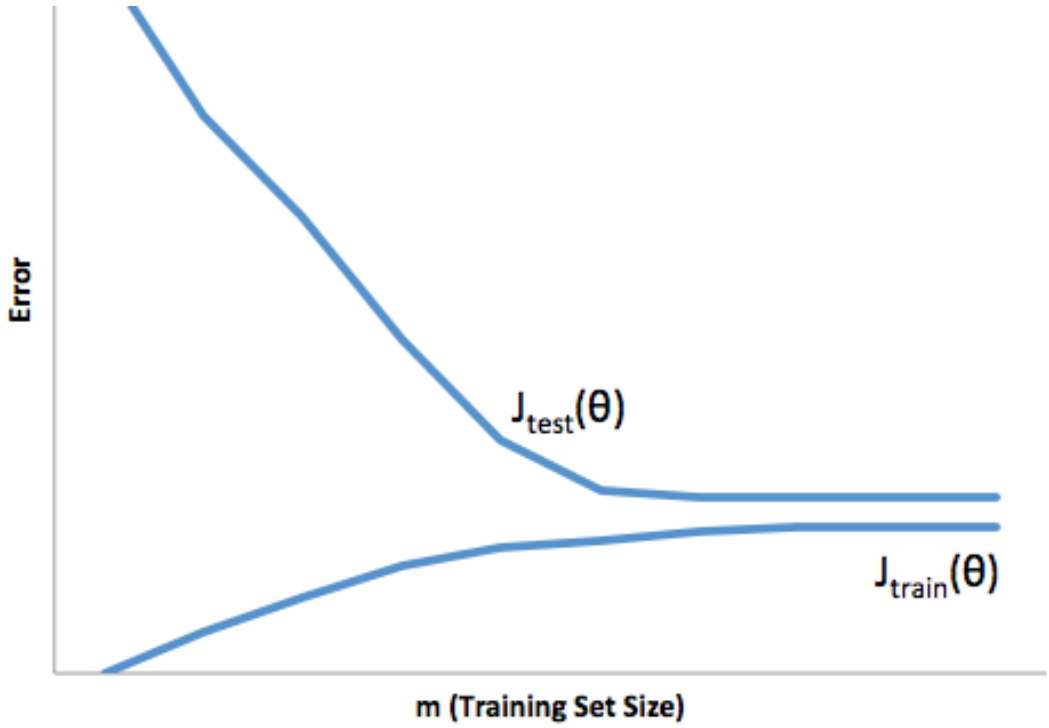

Figure 1.6: A high bias function is not complex enough to approach the generator function closely.

The function on the rights The function on the right corresponds to an overfit; the function 'goes through' each point exactly, but one can see that in between data points the behaviour of the hypothesis function is not logical. This problem is known as a high variance problem, where the train error is close to zero, but the test error is quite dramatic.

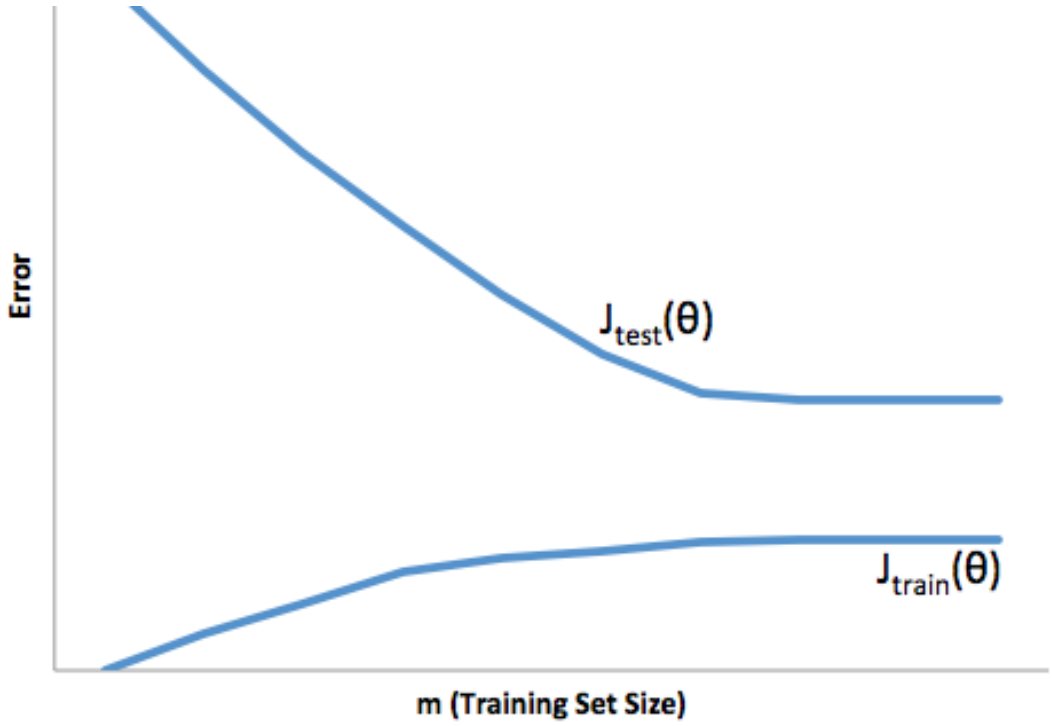

Figure 1.7: A High variance function is too complex and fits the data point too closely.

Another way to explain the bias variance tradeoff is by an example. Suppose you have a dart board, as shown in Figure 1.8. Suppose the situation on the top left corner, this corresponds to a world class player that has perfect aim, and very little variation on his precision. The situation on the left bottom corresponds to a player that has very little variation on his precision, but that is consistently aiming too high, he is biased to hit higher than needed. The pictures on the right side are different, there the person may or may not have a biased aim, but it is clear that he has a lot of variation in the precision of his aim.

In the context of machine learning, the low bias corresponds to having a hypothesis set that is close to the generator function, which allows you to get quite close. However you still have to pick the right function from that set, which is hard to do if you don't have enough data. If you are not able to take the best solution from the hypothesis set, you have high variance.

Figure 1.8: The bias variance explained using the dartboard example found at [17]

1.3.2 Support Vector Machines (SVM)

1.3.3 Random Forests (RF)

1.4 Goal of the thesis

The first goal is finding relevant features for emotion recognition in a person specific setting. This algorithm tries to accurately predict the emotions of one person, using only training data from that person. The Second goal is finding features for emotion recognition in a cross-persons setting. In this setting the features should generalise well across different persons, thus the algorithm should be able to recognize emotions from unseen persons.

The main problem is that there are already a lot of features known, but, as is often the case with EEG data, training data is expensive and limited. Using a lot of features will thus quickly result in overfitting.

Additionally, a lot of different features are reported in the literature, as you can see in Table 1.1.

Table 1.1: Six different papers on emotion recognition, six different feature sets

study	features used
[18]	Alpha and beta power
[19]	PSD and asymmetry features
[20]	PSD
[21]	discrete wavelet transform of alpha, beta and gamma band
[2]	alpha/beta ratio, Fpz beta and alpha band power
[11]	PSD, RCAU, DCAU, DASM, RASM, DE

Another point to note is that simply using a limited set of features, might work, but is likely to lead too less accurate results as optimal features might have been left out. This problem is even more severe when considering that EEG data is person specific, features that work good for one person, might not work for another person. Finding a good set of features that works for all persons is a non trivial problem. One solution to this problem could be to use a large pool of possible features from which a limited set of good features are selected. This allows to provide good features to the machine learning algorithm, while still keeping the set of features limited in size. The machine learning algorithm which features to use and which to neglect.

1.4.1 Dataset

One of the most used datasets in the context of emotion recognition is the Dataset for Emotion Analysis using Physiological Signals (DEAP) dataset[14]. This dataset contains EEG samples at 512 Hz of 32 persons each viewing 40 videos. A preprocessed version of this dataset, that is down sampled to 128Hz and has EOG removal will be used extensively during this thesis.

2

Feature Selection methods

This section will first explain what feature selection means and why it is used, before giving a detailed overview of the different methods.

2.1 Feature selection

Feature selection is the process of selecting good features from a set of feature. The need for this is twofold: first by reducing the number of features, you can protect yourself against overfitting. This is important when the dataset is limited. Second, reducing the number of features can speedup the learning process of a learning algorithm as fewer parameters need to be optimized. Additionally, in the context of research and this thesis, looking at which features are important gives insight in the problem. In the context of this thesis, knowing what feature are relevant can help neuroscientists understand the working of the brain better.

2.1.1 Pearson correlation

The Pearson correlation coefficient measures the linear relationship between two variables. The output is a value r, that lies between -1 and 1, corresponding to perfect negative correlation and perfect positive correlation respectively. A correlation value of 0 means that there is no correlation.

More formally[22], the Pearson product-moment coefficient of correlation, r between variables X_i and Y_i of datasets X and Y is defined as:

$$r = \frac{SS_{xy}}{\sqrt{SS_{xx}SS_{yy}}}$$

with

$$SS_{xy} = \sum_i (X_i - \tilde{X})(Y_i - \tilde{Y})$$

and

$$SS_{xx} = \sum_i (X_i - \tilde{X})^2$$
$$SS_{yy} = \sum_i (y_i - \tilde{Y})^2$$

The Pearson correlation coefficient is fast and simple to calculate, but has some major shortcomings. First off, it can only see linear relation ships and will not see the correlation between a value x and x^2.

In the context of this thesis, whether the correlation is positive or negative is not important; a learning algorithm needs features that have significant correlation. As a result the absolute value of the r value is reported as this allows for faster comparison of correlations.

2.1.2 mutual information

Mutual information is a more robust option for correlation estimation. The mutual information, I, of two variables X and Y is defined as [23]:

$$I(X,Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) log(\frac{p(x,y)}{(x)p(y)}$$

Using the mutual information directly for feature ranking might be inconvenient for two reasons. Firstly, it doesn't lie in a fixed range and it is hard to compute for continuous variables. One solution for this problem is to normalize the mutual information scores, so that the results lies between 0 and 1.

The normalized mutual information, NMI of variables X and Y is given by:

$$NMI(X,Y) = \frac{H(X)+H(Y)}{H(X,Y)}$$

With $H(X)$ and $H(Y)$ being the Shannon entropy of variable X and variable Y, defined as:

$$H(X) = \sum_{i \in X} p_i log(\frac{1}{p_i}) = -\sum_i p_i log(p_i)$$
$$H(Y) = \sum_{i \in Y} p_i log(\frac{1}{p_i}) = -\sum_i p_i log(p_i)$$

2.1.3 distance correlation

Distance correlation is a relatively new technique that is designed explicitly to address shortcomings of Pearson correlation. A Pearson correlation coefficient of zero implies that the variables might be independent, but as mentioned before, does not guarantee this.

The distance covariance is defined as[24]:

$$dCov^2(X,Y) = \frac{1}{n^2} \sum_l imits_{k,l=1}^n A_{k,l} B_{k,l}$$

With A, B being simple linear functions of the pairwise distances between sample elements. This metric is a covariance metric, which means that it is not normalized. The distance correlation is the normalized version of the distance covariance and is defined as:

$$dCor(X,Y) = \frac{dCov(X,Y)}{\sqrt{dVar(X)dVar(Y)}}$$

With $dCov(X,Y)$ being the aforementioned distance covariance, $dVar(X)$ and $dVar(Y)$ are the distance standard deviations.

The distance correlation has the disadvantage that is much slower than mutual information or Pearson correlation, but in return, the distance correlation is able to detect more complex relationships between two variables.

2.1.4 Linear Regression

Another way of finding relevant features is to use model based ranking. In model based ranking an arbitrary machine learning method is used to build a model. Looking at the coefficients of the trained model, the importance is determined by its own coefficient. High coefficients mean that the feature has a lot of influence on the output, while low coefficients correspond to less important features.

The first method to use is simple linear regression. This method tries to find a linear combination of features that produces the output value. Linear regression can achieve good results given that the data doesn't contain a lot of noise and the features are (relatively) independent. When the set of features contains correlated features, the model becomes unstable. As a result, small changes in input data might lead to huge differences in output coefficients. for example assume the 'real output' is given by $Y = X_1 + X_2$ and the dataset contains output in the form of $Y = X_1 + X_2 + \epsilon$ with ϵ being some random noise. Further more assume that X_1 and X_2 are linearly correlated, meaning that $X_1 \approx X_2$. The suspected output of the model should be $Y = X_1 + X_2$, but since noise is added the algorithm might end up with arbitrary combinations of X_1 and X_2, e.g. $Y = -X_1 + 3X_2$ and rate one feature much higher than another one, while in reality they are of equal importance. This is due to the noise; by maximizing the performance, the algorithm will minimize the influence of noise on the output, which result in unstable behaviour when sufficient correlated features are present.

2.1.5 Lasso Regression

Lasso regression uses L1 regularization, that adds a penalty $\alpha \sum_{i=1}^{n} |w_i|$ to the loss function. the result is that the coefficients of weak features are forced to zero, as each non-zero feature adds to the penalty. This form is regularization is thus quite aggressive, it removes weak features completely. The problem with this is, again, stability; coefficient can vary significantly even for small changes in training data, when there are correlated features.

2.1.6 Ridge Regression

Ridge regression uses L2 regularization, which add a L2 norm penalty to the loss function, given by $\alpha \sum_{i=1}^{n} w_i^2$. Where the L1 norm forces the coefficients to zero, the L2 regularization forces the coefficients to be spread out more equally. The result is that correlated features tend to get similar coefficients, as this minimizes the loss function, which in turn results in a more stable model.

2.1.7 SVM

Just like Regression uses linear regression to get coefficients, it is also possible to use SVM for feature importance estimation.

2.1.8 Random Forests

Random forests (RF) is a efficient learning algorithm based on model bagging and aggregation ideas[25]. The Random forests work by creating different decision trees. On their own, decision trees are very prone to overfitting. Random forests solve this problem by creating an aggregation of trees.

Additionally, some randomness is included, each tree looks at a random subset of the samples and a random subset of the features. This principle is shown in Figure 2.1. This random subset of samples is called the bootstrap sample and is selected out of N samples, by picking N times a sample, with replacement. This results, on average, in 2/3 of the samples being selected (with some doubles). The other 1/3 of the samples are then used as out of bag (oob) set. Averaging the performance of each tree on the out of bag set, offers an indication of the generalisation of the random forest.

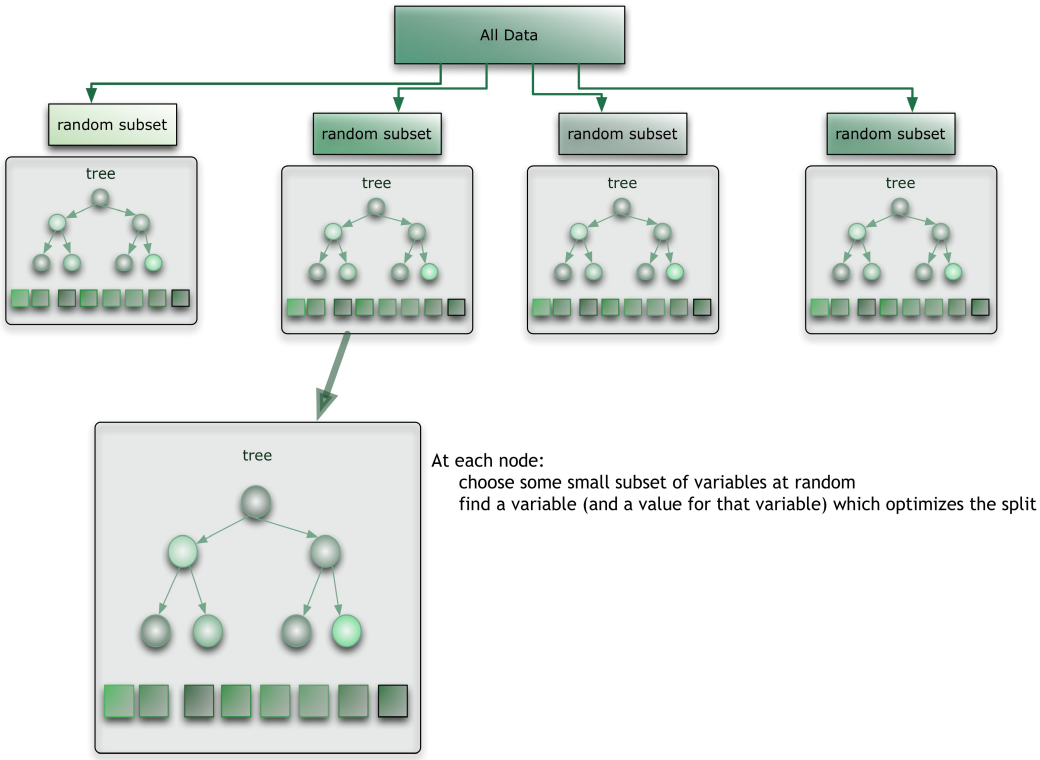

Figure 2.1: The structure of a random forest, found at [26]

To understand which features are good, one needs to understand the internal workings of a decision tree. Suppose the following example[1], where one tries to find an algorithm to predicted whether or not a person will play tennis on a given day. Suppose the training data is given by Table 2.1 and a prediction for the 15th sample needs to be made.

[1]This example is based extensively on this youtube video: https://www.youtube.com/watch?v=eKD5gxPPeY0

Table 2.1: suppose the following training examples for a decision tree.

Day	Outlook	Humidity	Wind	Play tennis
1	sunny	high	weak	no
2	sunny	high	strong	no
3	overcast	high	weak	yes
4	rain	high	weak	yes
5	rain	normal	weak	yes
6	rain	normal	strong	no
7	overcast	normal	strong	yes
8	sunny	high	weak	no
9	sunny	normal	weak	yes
10	rain	normal	weak	yes
11	sunny	normal	strong	yes
12	overcast	high	strong	yes
13	overcast	normal	weak	yes
14	rain	high	strong	no
15	rain	high	weak	?

A decision tree will take a feature and split the data based on the possible outcomes of this feature. In case the features are continuous values, ranges are selected. In some cases the leafs will be pure, like the leaves displayed in green in Figure 2.2. All examples in here have the same output. In case the leave is not pure, then another split is needed. Note that not all random forests split until all leaves are pure; random forest can be limited in depth, in that case the output is chose by a majority voting of the samples.

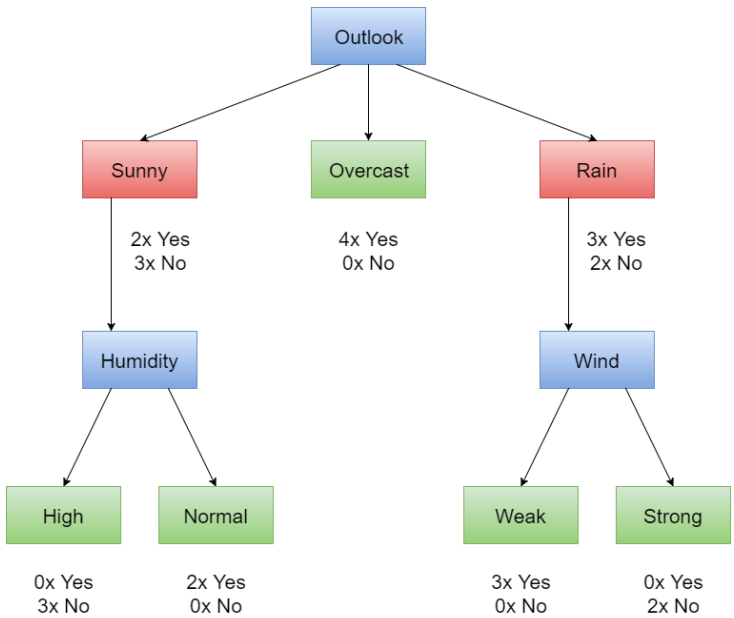

Figure 2.2: A decision tree for the data in Table 2.1

Once the tree is constructed it becomes clear that the predicted output of sample 15 is yes. This is obtained simply by following the tree branches. Even though the features are selected at random, they have influence on the accuracy. Good features will reduce the impurity significantly, thus the impurity reductions are a good indication for how important a feature is.

Since the importance is averaged over different nodes and different trees, it is also capable of detecting combinations of features that work well. One feature may not be important on its own, but might be a very good feature when combined with other features. Suppose the following example in Table **??**:

label	**feature A**	**feature B**
Happy	+	+
Happy	-	-
Sad	-	+
Sad	+	-

Table 2.2: Some feature are not significant on its own, but a might be part of a combination of features.

It is clear that feature A and B are very important when it comes to predicting whether or not a person is happy or sad. When both features have the same sign, the person is happy, otherwise he is not. This problem occurs in many simple selection methods.

This problem does not occur for random forest though, as combinations of features are also 'tested' in the sense that a tree might split on them in different stages. Once the combination of features occurs randomly in a decision tree, the impurity will drop significantly, which will result in higher importance rankings.

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