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Recognize Emotion using EEG Data

by

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Contents

Nomenclature

ANET Affective Norms for English Text

ANEW Affective Norms for English Words

CSEA Center for the Study of Emotion and Attention

DEAP Dataset for Emotion Analysis using Physiological Signals

EEG Electroencephalography

ERP Event Related Potential

Fm Frontal Midline

IADS International Affective Digital Sounds

IAPS International Affective Picture System

MEG magnetoencephalography

SAM Self-Assessment Manikin

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1

Introduction

1.1 The P300 speller

The basic version of P300 speller uses a six by six grid of characters, each row and column is flashed in a random order while the subject silently counts the number of flashes of a certain character, as shown in figure 1.1. This procedure, where a train of stimuli with some infrequent occurring target stimuli is applied, is called the oddball paradigm. The technique triggers an increase in potential difference in the EEG around the parietal lobe. This Event Related Potential (ERP) occurs +- 300 milliseconds after the stimuli is flashed and is called the P300 waveform[15]. The presence or absence of the P300 waveform is used by the P300 speller to determine what character the subject was focusing on, which allows the subject to spell text.

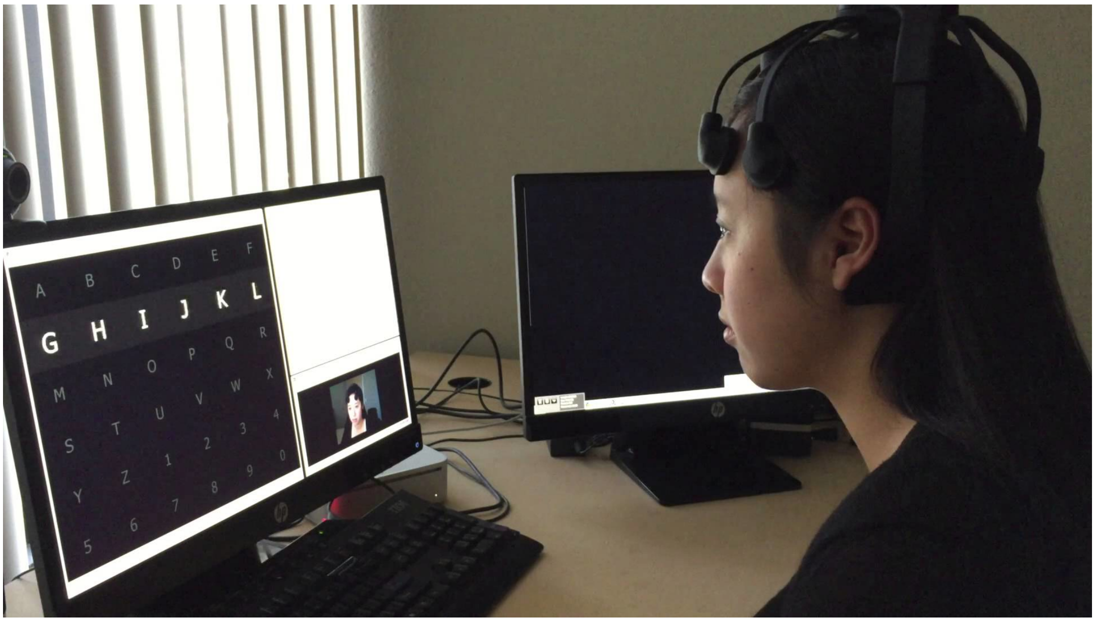

Figure 1.1: Different parts of the P300 speller, found at [6].

To improve the spelling time many improvements and research has been done. Language models were developed that predicted the word achieved great speedups[24], classifiers were compared and tested on both healthy[12] and unhealthy subjects[15]. Since many unhealthy subjects might have an impaired vision or eye movement, tactile[4] and auditory[8] spellers have been developed.

To improve accuracy, common problems such as adjacency distraction, when a subject is distracted from a neighboring flash, and double flashes, when the target row and column are flashed close after each othert, were avoided using new randomized paradigms[23]. Other input layouts like the T9 interface P300 speller have also been developed[1].

To further speedup the spelling, Error potentials were explored[7]. Error potentials are triggered when the user becomes aware of en erroneous action, i.e. when a wrong character is selected. When an Error potential is detected, the character is usually changed to the second most probable character according to the P300 decoding[5], this is the most likely character.

1.2 Benefits of creating an emotionally aware P300 speller

Emotions play a major role in non-verbal communication, are quite complex and essential to understand human behavior. The ability to recognize emotions will improve the ability of computers to understand human interaction[17] and thus improve the P300 speller's accuracy.

1.2.1 Aid in Error potential detection

To improve the detection of error potentials, emotion can be used. It is expected that when a person makes a lot of mistakes, his/her emotional state will change to a less happy, more frustrated state. Making the speller emotionally aware, could improve the detection of error potentials.

1.2.2 Effect on the P300 wave

Research with visual stimulus on healthy subjects, show that emotion has an effect on the auditory P300 wave[16]. Both the P300 peak amplitude and area was highest when viewing neutral pictures and descended further, in decreasing order, for sadness, anger and pleasure. The amplitudes were significantly lower at both Fz and C3 positions than Pz and Oz. The latency of the P300 ERP speller was shortest or neutrality and in increasing order longer for pleasure, anger and sadness. Interestingly, the P300 amplitudes were significantly larger for woman than for men. Additionally women showed lower amplitudes for for pleasure than neutrality or sadness while man showed smaller amplitudes for pleasure then either neutral or sadness.

1.2.3 Ethical issues

Detecting emotion can also help in more ways than just improving spelling speed. Knowing what the subject feels, can help him communicate more humane while providing more insight for ethical issues, e.g. "How does the subject think about the P300 speller recording and analyzing his brain activity?".

2

Emotion in the brain

How does one define emotion? In psychology a clear distinction is made 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, 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[13].

2.1 Brain Computer Interface (BCI) basics

2.1.1 Electroencephalography

Different technologies exist to analyse 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 of the brain using electrodes placed on the scalp.

Signals originating from the cortex, close to the skull, are most visible. 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, that has to be removed. Even though the noise is persistent and has very low spatial resolution, EEG data can provide significant insight into the electrical activity of the cortex while offering excellent temporal resolution[9].

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, shielding is required, making this method less preferable.

2.1.2 Electrode positioning and types

As mentioned before, electrodes 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[21]. 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 the 10/20 system is added below for clarification. Note that some experiments may use more channels than shown in figure 2.1, but they all follow the same naming convention.

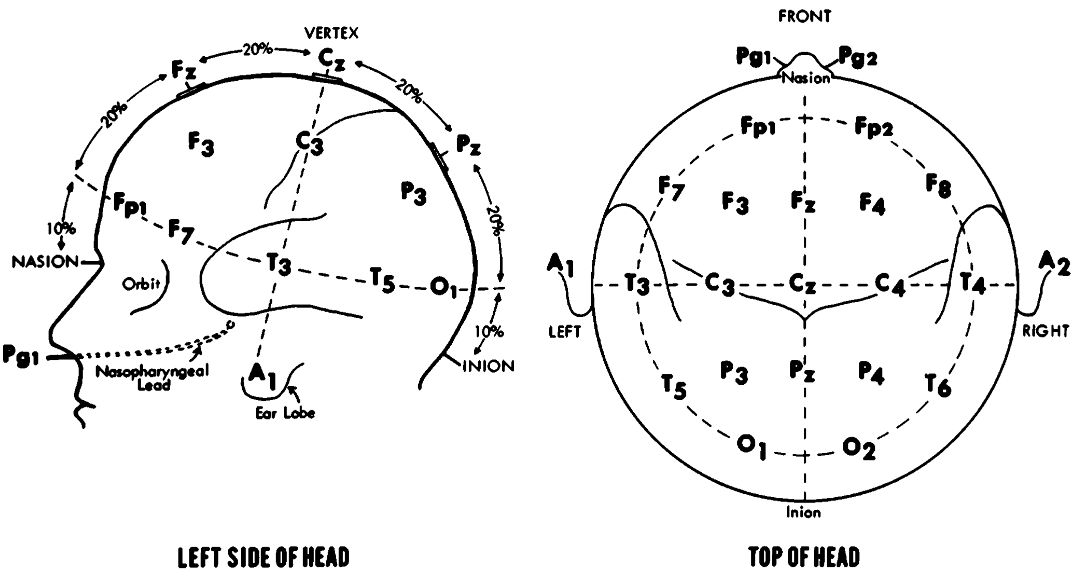

Figure 2.1: The electrode placement system[22].

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[25].

2.1.3 Event related potentials

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. It is this activity that is measured by the surface electrodes.

An Event related potential (ERP), is a measured brain response to an event, measured by EEG or MEG. The ERP nomenclature usually starts with a letter that indicates the polarity: the P corresponds to a positive polarity, while the N indicates a negative polarity. The number indicates the mean latency, which might may variate significantly between subjects.

The most important one is the P300 wave, which is usually elicited using the oddball paradigm; when a low probability target item occurs between high probability items. It consists of two components, the P3a with a latency of 240ms and the P3b with a latency of 350 ms[19]. The later component, P3b only occurs when the subject actively counted either the targeted or more frequent stimuli.

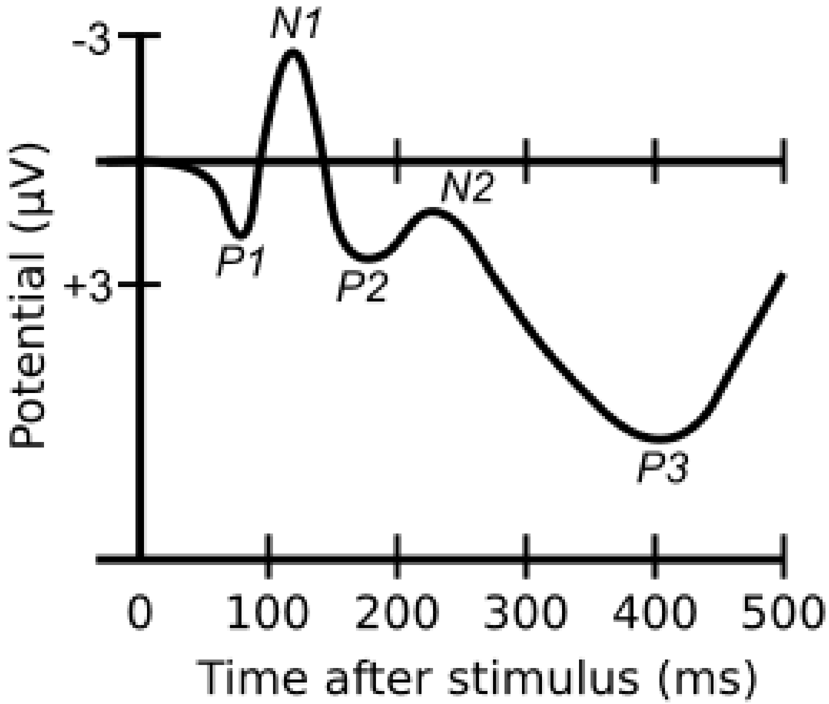

Figure 2.2: The Different ERP linked to an oddball paradigm.

2.1.4 Brain waves

Usually, brain waves are split into different bands, based on their frequency[10][3].

1. **Alpha:** 8-13Hz, indicate that the brain is relaxed and/or inactive.
2. **Beta:** 13-30HZ, point to a more active and focused brain.
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

To remove most muscle and eye artifacts have a frequency around 1.2Hz, and artificats caused by nearby power lines, with a frequency of around 50Hz[2], usually a bandpass filter is applied to filter out frequencies below 4Hz and above 40-45Hz. This already removes a lot of noise from the data.

2.2 Extracting emotion from EEG data

2.2.1 Arousal - valence (- dominance) classification

Before emotions can be recognized, a classification model is needed. A common model to classify emotions is the bipolar arousal-valence model[2][14], that places emotions in a two dimensional space. The main advantage of using a multidimensional model, is that all emotions are modeled in its space, even when no particular label can be used to define the current feeling. Figure 2.3 shows the mapping of different emotions for this model.

Sometimes a third dimension is added, the dominance, an indication for how strong the emotion is perceived [13]. Note that this dimension is less important for the emotion classification. To summarize, the three dimension are:

1. **Valence:** whether or not the emotion is perceived as positive or negative.
2. **Arousal:** measures how excited or calm a person is.
3. **Dominance:** how strong the emotion is perceived.

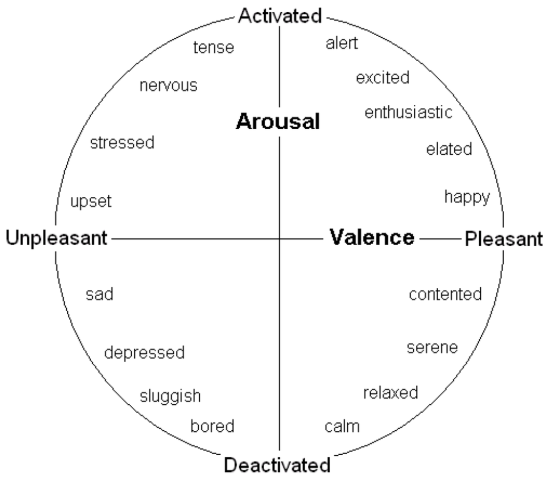

Figure 2.3: The arousal - valence model maps emotions in a two dimensional plane.

2.2.2 Determining arousal

Arousal can be determined in several ways. A first methods for the arousal recognition uses only alpha and beta bands. the Alpha band corresponds with a relaxed state and is often connected to brain inactivity[2][14]. Beta waves, on the other hand, are an indication that the brain is a more active state or has a higher level of arousal. Combining these two parameters gives the beta/alpha ratio as an indication of the arousal level.

EEG coherence across prefrontal and posterior beta oscillations is known to increase when high arousal images are viewed. Additionally, the gamma power around 46-65Hz increase with arousal with a delay of 500ms.

2.2.3 Determining valence

An often reported features is the frontal asymmetry of the alpha power[9]. The right hemisphere is generally speaking, more active during negative emotion than the left hemisphere which is in turn more active during positive emotions[14][13]. The assymmetry is given for L and R being the Left and Right frontal alpha powers as:

$$Index = \frac{L-R}{L+R}$$

Computing the spectral power of the alpha band is possible via e.g. the fast fourier transform or wavelet transform. Some papers also include the left and right anterior temporal lobe channels.

It is also possible to include beta waves in the process. High alpha rates correspond with an inactive brain, while high beta waves with an active brain. Looking for an increase in beta activity and a decrease in alpha activity at one side, while the other hemisphere should show an increase in alpha waves and a decrease of beta waves as indication that is becomes less active, offers an insight to the valence[2].

Another features is the frontal midline (Fm) theta power, that is shown to increase with increasing pleasant ratings for audio stimuli[18]. Gamma phase synchronization increases for unpleasant images.

2.2.4 Datasets

One of the most used datasets is the Dataset for Emotion Analysis using Physiological Signals (DEAP) dataset[11]. 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 and has EOG removal was used extensively during this thesis.

Furthermore, the center for the study of emotion and attention (CSEA), by the university of Florida made several visual datasets available:

- **IAPS:** International Affective Picture System
  This dataset consists of a large set op emotional stimuli in the form of color photographs.
- **IADS:** International Affective Digital Sounds
  This dataset consists of acoustic emotional stimuli designed for investigation and research of emotion and attention.
- **ANEW:** Affective Norms for English Words
  This dataset provides a set of emotional ratings for a large number of english words.
- **ANET:** Affective Norms for English Text
  This set provides normative ratings of emotion for a large set of brief texts.
- **SAM:** Self-Assessment Manikin
  A non-verbal pictorial assessment technique that measures the pleasure, arousal and dominance associated with a person's affective reaction to a wide variety of stimuli.

The stimuli from these sets are often used in experiments to trigger emotions[2][20][14][13].

Bibliography

[1] F. Akram, Hee-Sok Han, Hyun Jae Jeon, Kyungmo Park, Seung-Hun Park, Jinsung Cho, and Tae-Seong Kim. An efficient words typing p300-bci system using a modified t9 interface and random forest classifier. In *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pages 2251–2254, July 2013. doi: 10.1109/EMBC.2013.6609985.

[2] Danny Oude Bos. Eeg-based emotion recognition. 2007.

[3] Brainworks. What are brainwaves?, 2015. URL `http://www.brainworksneurotherapy.com/what-are-brainwaves`.

[4] Anne-Marie Brouwer and Jan B.F. van Erp. A tactile p300 brain-computer interface. *Frontiers in Neuroscience*, 4(19), May 2010. doi:10.3389/fnins.2010.00019.

[5] Ricardo Chavarriaga, Aleksander Sobolewski, and JosÃ© del R MillÃ¡n. Errare machinale est: The use of error-related potentials in brain-machine interfaces. *Frontiers in Neuroscience*, 8(208), 2014. ISSN 1662-453X. doi: 10.3389/fnins.2014.00208. URL `http://www.frontiersin.org/neuroprosthetics/10.3389/fnins.2014.00208/abstract`.

[6] Cognionics. Cognionics dry eeg p300 speller demo, 2015. URL `https://www.youtube.com/watch?v=XIr2cRKFolY`.

[7] Aäron Coone. A study on different preprocessing and machine learning techniques for the detection of error-potentials in brain-computer interfaces. Afstudeerwerk, Ghent university, June 2011.

[8] Johannes Höhne, Martijn Schreuder, Benjamin Blankertz, and Michael Tangermann. Towdimensional auditory p300 speller with predictive text system. *IEEE EMBS*, 2010.

[9] Min-Ki Kim, Miyoung Kim, Eunmi Oh, and Sung-Phil Kim. A review on the computational methods for emotional state estimation from the human eeg. *Computational and Mathematical Methods in Medicine*, 2013(573734):13, 2013.

[10] Kwang-Eun Ko, Hyun-Chang, and Kwee-Bo Sim. Emotion recognition using eeg signals with relative power values and bayesian network. *International Journal of Control, Automation, and Systems*, 2009.

[11] S. Koelstra, C. Muhl, M. Soleymani, Jong-Seok Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras. Deap: A database for emotion analysis ;using physiological signals. *Affective Computing, IEEE Transactions on*, 3(1):18–31, Jan 2012. ISSN 1949-3045. doi: 10.1109/T-AFFC.2011.15.

[12] Dean J Krusienski, Eric W Sellers, François Cabestaing, Sabri Bayoudh, Dennis J McFarland, Theresa M Vaughan, and Jonathan R Wolpaw. A comparison of classification techniques for the p300 speller. *Journal of Neural Engineering*, 3(4):299, 2006. URL `http://stacks.iop.org/1741-2552/3/i=4/a=007`.

[13] Yisi Lio and Olga Sourina. Eeg databases for emotion recognition. *International Conference on Cyberworlds*, 2013.

[14] Yisi Lio, Olga Sourina, and Minh Khoa Nguyen. Real-time eeg based human emotion recognition and visualization. 2010.

[15] Nikolay V. Manyakov, Nikolay Chumerin, Adrien Combaz, and Marc M. Van Hulle. Comparison of classification methods for p300 brain computer interface on diabled subjects. *Computational intelligence and neuroscience*, 2011.

[16] Yoshifumi Morita, Kiichiro Morita, Masashi Yamamoto, Yoshifumi Waseda, and Hisao Maeda. Effects of facial affect recognition on the auditory {P300} in healthy subjects. *Neuroscience Research*, 41(1):89 – 95, 2001. ISSN 0168-0102. doi: http://dx.doi.org/10.1016/S0168-0102(01)00248-6. URL `http://www.sciencedirect.com/science/article/pii/S0168010201002486`.

[17] R. W. Picard and J. Klein. Computers that recognise and respond to user emotion: theoretical and practical applications. Interacting with computers(14):141–169, 2002.

[18] Daniela Sammler, Maren Grigutsch, Thomas Fritz, and Stefan Koelsch. Music and emotion: Electrophysiological correlates of the processing of pleasant and unpleasant music. *Psychophysiology*, 44:209–304, 2007. DOI: 10.1111/j.1469-8986.2007.00497.x.

[19] Nancy K. Squires, Kenneth C. Squires, Steven, and A. Hillyard. Two varieties of long-latency positive waves evoked by unpredictable auditory stimuli in man. *Electroencephalography and Clinical Neurophysiology*, pages 387–401, 1975.

[20] Mensia Technologies. Emotions by mensia, 2015. URL `http://www.mensiatech.com/emotions-mensia/`.

[21] Trans Cranial Technologies. *10/20 System Positioning manual*. Fortis Tower, 2012.

[22] unknown. Electrode placement, 2015. URL `http://aibolita.com/nervous-diseases/3647-electrode-placement.html`.

[23] Thibault Verhoeven. Brain-computer interfaces with machine learning: an improved paradigm for the p300 speller. Afstudeerwerk, Ghent University, June 2013.

[24] Hannes Verschore. A brain-computer interface combined with a language model: the requirements and benefits of a p300 speller. Afstudeerwerk, Ghent University, June 2012.

[25] Yuan Yang, Sylvain Chevallier, Joe Wiart, and Isabelle Bloch. Time-frequency optimization for discrimination between imagination of right and left hand movements based on two bipolar electroencephalography channels. *EURASIP journal on Advances in Signal Processing*, 2014(38), 2014.