A new paradigm for BCI research

A new paradigm for BCI research

Ian Daly and **Slawek J. Nasuto** and **Kevin Warwick**[1]

Abstract. A new control paradigm for Brain Computer Interfaces (BCIs) is proposed.

BCIs provide a means of communication direct from the brain t a computer that allows individuals with motor disabilities an additional channel of communication and control of their external environment.

Traditional BCI control paradigms use motor imagery, frequency rhythm modification or the Event Related Potential (ERP) as a means of extracting a control signal.

A new control paradigm for BCIs based on speech imagery is initially proposed.

Further to this a unique system for identifying correlations between components of the EEG and target events is proposed and introduced.

1 Introduction

Investigations into the possibility of creating a speech imagery based BCI are described. Such a BCI allows a degree of control of a computer system by the user without the need for muscle movement. Thus individuals with motor disabilities would be able to use the system to communicate and control their immediate environment.

A speech imagery based BCI has several advantages over traditional BCI control paradigms.

1. It's a more natural way for the user to communicate. Imagining words is a much more direct means of communication then imaging hand movements which is then used to control a cursor to (among other things) select letters to spell a word.
2. No training is required on the part of the user. This reduces setup time and increases user motivation.
3. It's a much more direct means of control for the user. Thus the user will have a greater level of success and hence be more motivated to use the system.

Towards this end it becomes necessary to identify correlations within the EEG between speech imagery of specific words and certain features of the EEG. Thus a unique solution to identifying these correlations is outlined.

Such a solution has numerous advantages to other researchers in the BCI field. Hence our motivation is to create a unique solution for identifying correlations between EEG features and specific tasks.

In researching such systems current methods within the BCI field are first identified.

1.1 Current BCIs - background

Traditional methods for interacting with computers are based on motor movement controlled interfaces. The most common of which are the keyboard and the mouse. However an expanding field of current research involves methods for directly interfacing between the brain and a computer, bypassing motor movement control. Such direct interfacing opens up the possibility for additional channels of communication and environmental control for individuals with motor disabilities.

It should be noted at this stage that systems interfacing with the brain can be classified as Brain Machine Interfaces (BMIs), where BMIs usually refer to invasive interfacing and signal extraction techniques, and Brain Computer Interfaces (BCIs), which commonly refer to noninvasive techniques [33]. However to avoid overly verbose language here we simply refer to all Brain Computer and Brain Machine Interfaces as BCIs.

BCI components can be broken down into five broad areas, these are.

1. Signal extraction.
2. Signal processing techniques.
3. Feature extraction.
4. Classification techniques.
5. Control paradigms.

Signal extraction refers to the reading of levels of neurological activity from individuals with the aim of extracting a useful control signal for our BCI. This can take two general forms, either invasive techniques such as implanted electrode arrays or non-invasive techniques such as the EEG.
Signal processing refers to the intermediate steps taken between extracting a signal and classifying it. The techniques that can be used here are many and vary significantly depending on the type of signal extraction method and specific hardware used. They can also depend on the intended usage of our signal. However the general aim is always to maximize the signal to noise ratio with respect to the features of the signal that are the most interesting and usable for our purposes.

Signal types within BCI encompass both the type of signal extracted and the way that signal is used. There are many different types of signals that can be extracted from the brain, these include EEG rhythms such as the mu rhythm (related to motor movement), neural firing spike trains (from invasive signal extraction methods), event related potentials and many more.

Classification follows on from signal processing. Classification attempts to determine whether a specific signal belongs to a specific class group. That is; what command or stimulus presentation a specific signal feature corresponds to.

There are two paradigms for control of BCI systems; control based paradigms and the goal based paradigms.

Goal based BCIs present a selection of options to the user. The user then chooses one of them as their target [33]. For example; in a BCI speller the subject will be presented with a selection of letters from which they select the one they want.

[1] University of Reading, UK, email: i.daly@reading.ac.uk

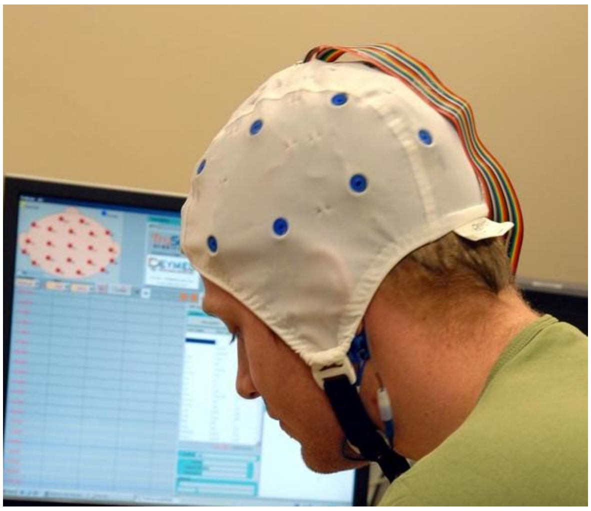

Figure 1. Figure 1.0 - Typical EEG recording

Control based BCIs by contrast allow the user to set their own goals [33]. For example; many motor imagery based BCIs such as [7] make use of this paradigm. With these systems the user attempts to position a cursor or prosthetic device in any location. Typically the cursor or prosthetic's velocity along one or more directional axis is controlled by the strength of some neurological signal component.

We can thus say that goal based BCIs are discrete, digital systems and control based BCIs are open, analog systems.

1.2 Neurolinguistics

Of key importance for attempts to develop a speech production based BCI is the current research into neurolinguistics. That is, research into the neurological mechanisms of speech perception and production. Therefore the following introduces relevant neurolinguistic concepts.

The key areas in the brain involved in speech are Broca's area which lies on the third convolution in the left brain hemisphere and was first identified by Paul Broca in 1861 [29]. This region has been shown to display activity during speech production in a number of studies using different imaging techniques such as EEG [5], fMRI [9] and various other functional neuroimaging techniques including the use of the ERP paradigm [31] and [21]. Furthermore studies on patients with lesions (localized damage to specific areas within the brain), located in or overlapping with Broca's area have been shown to have a correlation with speech motor difficulties [1].

We can thus say that imaging techniques such as the EEG have been shown to identify activity in specific brain regions during certain speech production related functions.

Carl Wernicke produced evidence in 1874 showing that an area of the brain located on the inferior parietal lobe (later to be known as Wernicke's area) consistently showed activity during speech perception [4]. Furthermore damage to this area caused speech perception difficulties in patients. Wernicke extended this work to produce a theory of a "language gyrus", an area of the brain comprising Wernicke's area, Broca's area and the pathways of communication between them. Damage to any region in this area would lead to aphasia (language disorders).

From this theory naturally emerges the idea of functional localization within the brain. That is, we attribute specific localized areas specific functions, Broca's area performs speech production, Wernicke's area speech perception and together they are responsible for language. This idea was further strengthened by the formulation of a much more detailed model of the different specialized areas of language localization within the brain by Salomon Henschen in 1926 [15]. This model was based on previous clinical studies of patients with aphasia and the specific localization of lesions within their brains. The model has been elaborated on in further studies with even more specific sites added to the map of the brain developed by Brodmann [20].

It's important to note that there can be said to exist a level of localization of function within the brain. For example damage to Broca's area will most likely result in loss of speech production abilities, although the extent of the loss of function and which specific speech functions are lost is still the subject of much research. It can however be said with a very high level of confidence that when a subject speaks a high level of activity will occur within Broca's area and when a subject listens to speech a high level of activity will occur within Wernicke's area. Furthermore it has been shown that this activity can be detected via EEG [6] using wavelet decomposition and independent component analysis to reveal high levels of EEG activity within certain components at times corresponding to speech perception.

Other research into EEG analysis of language has shown a level of similarity between the mental rehearsal (imagination) of a language function and it's implementation [5]. This is akin to the level of similarity exhibited between the mental imagery of a motor function and it's implementation [19]. It is upon this principle that the majority of the current BCI research into motor control is based.

Additionally fMRI is shown to exhibit specific activity patterns during linguistics tasks such as word perception and production. Analysis of EEG using fuzzy logic to classify wavelet decompositions of the signal is shown to correctly classify speech imagery tasks fr three simple nouns (colour names; red, green and blue). This demonstrates that it is possible to use a range of imaging techniques to identify neurological processes related to speech perception and production. Further to this it is possible to correctly identify the perception and imagined production of different words in the EEG.

It is therefore reasonable to hypothesize that a BCI based upon the imagination of speech production is a feasible area of research.

2 Methods

To investigate speech based BCIs it is necessary to first asses whether stimuli presented to subjects can be recognized from their EEG. A series of papers ([25], [28], [26], [27] and [24]), propose a method that recognizes images presented to subjects from the EEG. These papers also report internal speech can be recognized from the EEG. These methods are therefore of great interest. However there are problems; most notably a validation set is not used to cross-check results achieved on the training set.

Therefore an investigation is made into the validity of this method with an independent data set [18]. The results of this investigation are explained below.

Further to this EEG recordings are made of subjects in the speech perception and speech imagery condition. This data will help to identify when subjects percieve/imagine producing specific words. These recording methods are also discussed below.

A research group headed by Philip Kennedy [30] is attempting to recognize phonemes produced by a subject with implant data recorded from a locked in patient. Comparisons with the results of this investigation are therefore very relevant. The experimental paradigm for investigating the perception and production of phonemes is directly translatable into researching the perception and production of words in the EEG and is therefore adapted for this purpose. This is described below.

2.1 Recognition of presented stimuli

The methods presented in a series of papers [25], [28], [26], [27] and [24] are investigated. A good rate of recognition of words presented to, and spoken by, subjects (both silently and overtly) is reported [25]. Similarly high recognition rates for sentences presented orally to the subject and words presented visually are reported to be high [28].

Additionally high recognition rates for images presented to the subjects are described [26] and [27]. A high level of invariance in the brains representation of words, sentences and stimuli is also described [26], [27] and [24]. This is contrary to common understanding of the brains representation of words and stimuli which states that the representation of such stimuli within the brain signal exhibits a large degree of variance over time and over different subjects [22].

As we recall from neurolinguistics research there exists a level of localization within the brains representation of linguistic functions. The extent of this localization is not however clearly defined. Representation of cognitive states can therefore be considered to be variant. This means it's representation varies within a loosely defined physical region of the brain.

2.1.1 Operations

The method performs the following operations.

1. Templates are generated from recordings of the subjects EEG while exposed to a stimuli.
2. Waveforms recorded during a series of stimuli presentations are taken as a training set.
3. Training and template waveforms are pass-band filtered.
4. If the smallest Euclidean distance is between the template and a waveform for the same stimulus as that template then this is taken as a correct recognition.
5. Steps 2 to 6 are performed across a set of waveforms.
6. For each pass band in the range of 1 to 40Hz a recognition rate is obtained. Hence the frequency range that gives the highest recognition rate for the target stimuli can be seen.

There are some problems with these methods as they have been presented. The most crucial of these is results are only presented for the training data. It is well understood in machine learning that good results in the training set do not necessarily translate to good results when applied to an independently generated validation set.

Therefore an attempt is made to validate these methods with an independent data set. Data is taken from the EPFL data sets used by Ulrich Hoffmann [32] for this purpose.

2.1.2 Results

The confusion matrices in Figure 1.0 show the presented stimuli against the classification results.

Training data							
		Target stimuli					
		TV	Phone	Lamp	Door	Window	Radio
Classifier result	TV	205	16	0	12	11	12
	Phone	13	206	0	8	15	14
	Lamp	2	1	251	0	1	1
	Door	11	17	1	204	13	10
	Window	6	14	3	9	212	12
	Radio	15	11	1	9	13	207

Figure 2. Figure 2.0 - Confusion matrix results for training set

Verification data							
		Target stimuli					
		TV	Phone	Lamp	Door	Window	Radio
Classifier result	TV	63	50	4	52	42	45
	Phone	54	58	5	47	42	50
	Lamp	10	10	212	6	12	6
	Door	48	49	6	53	39	61
	Window	50	49	9	44	52	52
	Radio	46	39	7	49	56	59

Figure 3. Figure 3.0 - Confusion matrix results for verification set

When applying these trained parameters to a validation set a much lower level of recognition is achieved for all stimuli except the third stimulus (a picture of a lamp). The lamp is recognized at a statistically significant rate of p ¡ 0.01. However the other stimuli where recognized at a rate of statistical significance of almost p = 1.0. Thus they are recognized at the same rate had no classification been occurring and the results are being just picked randomly.

The recognition of one stimuli out of 6 in the majority of cases indicates that there may be some potential from this method. However recognition of 1 out of 6 stimuli is not the ideal case.

2.2 Word perception/production

EEG is recorded from 20 subjects during the speech perception and the internal or covert speech production condition. This is done with the following aims.

1. Provide a large data set to act as a test bed for further research.
2. Identify any unique features related to subjects listening to language.
3. Identify any unique features related to subjects producing language.
4. Identify if we can distinguish between different words within the EEG when a subject is listening to or producing specific words.

This extends the research into methods for identifying visual stimuli presented to a subject. However a different approach will be taken to analyzing the data from that presented in [25], [28], [26], [27] and [24].

The experimental paradigm used for recording this data is based on the method described in [10] and originally proposed by Philip Kennedy's team. This ensures an accepted experimental paradigm is used and allows meaningful comparison of results with those obtained by Philip Kennedys group.

The experimental paradigm can be broken down into the following steps.

1. A listen instruction is presented to the subject. This is a pre-recorded voice to ensure it is identical across trials and subjects'it takes the form "Listen".
2. One stimulus audio waveform from a set of 6 different pre-recorded nouns is presented to the subject.
3. A pre-recorded speak instruction will be presented to the subject. This takes the form "Speak".
4. The subject then has a fixed period of time to "speak" the stimuli they where presented. All speech takes place internally, i.e. silently. Subjects are instructed to try not to make any muscle movements or blink during the course of the experiment so as to minimize interference from EMG activity and blink artifacts.

Stimuli is presented in random order from a list of pre-recorded voices. This ensures that the same stimuli retain the same characteristics across multiple trials. The randomized order ensures that subjects don't become overused to hearing a particular stimulus or able to predict future stimuli.

Stimuli is in the form of individual words of similar linguistic characteristics (short nouns). The experimental paradigm allows recording of both speech perception and speech production within the same trial.

Each trial lasts 5000ms. Trials are run consecutively in a session with each trial presenting different random stimuli from a pre-defined set. Stimuli presented in each trial is recorded along with additional relevant notes.

After every three stimulus presentations a pause is given. The subjects are instructed to use the pause to blink and adjust their position to keep themselves comfortable. This is an addition to the method in [10] and is added to account for the fact that the subjects need to move and blink occasionally to maintain comfort and alertness.

Trial sessions last 6 minutes to ensure subjects do not become overly tired or bored. There where 15 sessions in total. Frequent breaks between sessions are offered to the subjects. All the sessions for a single subject occurred on the same day.

3 Ongoing work

Ultimately a correlations looked for between the linguistics stimuli, the imagination of the production of these stimuli and the neurological activity as seen through the EEG that is time-locked to these events. Therefore of key importance to developing a speech BCI is producing a method to automatically identifies correlations between features of the EEG and time-locked events. An outline of our unique proposed method is described below.

Much of this research aims to produce greater understanding of classification methods and the way language is processed in the brain.

3.1 Data cleanup

As a pre-processing step it is necessary to remove eye blinks and EMG artifacts from the data. Artifact data arises from electrical activity with other causes to neurological activity. It often has little or no correlation to the neurological events we're interested in.

Blinks and EMG data both have large profiles in the signals time domain and need to be removed before many methods, such as the ERP, can become meaningful. Such removal schemes must meet the following criteria.

1. They must be consistent across different data sets.
2. They must be automatic.
3. They must have a high accuracy rating. Too many false positives or false negatives reduces the confidence with which the final data set can be treated.

Methods being investigated for cleaning of the EEG data include the blink filter described in [23] and investigations into other blink and EMG artifact filtering techniques such as linear trends and ICA based methods.

3.2 Feature extraction

There are many techniques available for feature extraction. These include Principal Component Analysis (PCA) [13] which attempts to identify the features of a given set of signals with the maximum variance. Thus PCA can be used in conjunction with other feature extraction methods to help identify the most suitable features for classification across different stimulus presentations. PCA has been used widely in BCI research and with some considerable success such as in [14] and [16].

Additionally Independent Component Analysis (ICA) has been used in neurolinguistics with some success to identify the electrode channels with the highest variance when subjects are imagining phonemes [6]. ICA is similar to PCA but assumes a functional independence between the different components of a system.

Other methods include variants on the Fourier transform to translate the signal from the time domain to the frequency domain allowing the power of frequency components within the signal to be revealed. Such techniques can help reveal frequencies that have the largest variance cross different stimulus presentations.

Alternatively the wavelet decomposition acts to highlight certain time-frequency components of the signal by convolving the original signal with a wavelet basis function. Such techniques can help reveal local time-frequency specific information that is lost when using Fourier methods.

Both these signal decomposition schemes are considered for feature extraction from the data.

3.3 Classification

Cleaned EEG data is classified into groups according to the stimuli being presented to, or produced by, each subject during a trial. There are various methods that have been used to classify data in BCI systems. These included Bayesian classifiers as used in [2] and [12], Hidden Markov Models as used in [11] and [17], Support Vector Machines [3] and [8] and Neural Networks [12].

Hidden Markov Models (HMMs) have been used to successfully classify overt speech from recorded sound waves. This naturally suggests they could be suitable for classification of the neurological signals corresponding to speech as recorded from the EEG.

Furthermore HMMs model a stochastic process via a series of probabilistically connected states where each state generates an observation, or signal component based on a probability distribution. This makes them ideally suited to modeling stochastic processes with an underlying probabilistic process such as overt audible speech.

EEG signals are known to be non-stationary in nature [22] exhibiting a large degree of variance over different subjects. However if there is an underlying probabilistic model which produces these stochastic signals then a HMM could be a good tool to help identify it and subsequently classify it.

When training a HMM the model that best describes the system is the ideal case. This means identifying the model parameters which give the highest probability of the sequence of observations made from the system. In the case of the recorded EEG data the best HMM is the model that has the highest probability of coming up with identical observation sequences to those seen in experimentation.

This is known as the optimization problem and is non-trivial. When the optimal model for the signals representing a given stimulus has been found via optimization this model can subsequently be applied to classification of other signals that relate to the same stimulus.

4 Automated feature correlation identification

A unique solution is proposed here for use in identifying correlations in the EEG with speech imagery related tasks.

A combination of ICA and HMMs is used to model the Independent Components (ICs) of a signal time locked to stimulus presentation / speech imagery. ICs with a large degree of correlation to events are modeled with HMMs. This combination of techniques has several advantages.

1. ICA can be used to identify components of a signal that have a large correlation with time locked events. Thus it can be used to select the components that are most suitable for classification.
2. EEG signals are inherently variant and stochastic in nature. Therefore by extension components of these signals are also variant in nature. Thus a probabilistic model to classify the most suitable ICs of a signal is well suited to our needs.
3. Automated means for identifying and classifying correlations between time locked events and EEG components will allow for efficient identification of suitable components within the EEG for a speech imagery BCI.

Towards this end the following goals are to be met.

1. Suitable methods for the identification of optimal HMMs are to be identified.
2. Automated EEG artifact removal methods are to be developed.
3. Means for identifying correlations between Independent components and EEG events are to be developed and applied.

5 Summary

A new BCI paradigm has been proposed which uses the neurological processes related to speech perception and production as a more natural and intuitive way to interact with a computer. Such a system presents a potentially significant improvement over current BCI systems in terms of ease of use for the intended recipients.

A unique method for identification and classification of these signals is also proposed. Such a system uses ICA to identify potentially useful components of a signal that have a high correlation with time locked events of interest. Hidden Markov Models are then used to model these components and subsequently classify them.

As an initial step a rigorous investigation is conducted into methods proposed to identify and classify EEG data with a high correlation to time locked events such as image and word presentations [18]

The progression of this work aims to develop automated methods for component identification and classification using ICA and HMMs.

Such efforts will greatly assist other research efforts in the field of biomedical signal processing.

6 Conclusion

A summary of the research into a new paradigm for BCI systems using a unique new method for correlation identification and classification is presented. Relevant background material has been introduced and relevant results obtained in the course of this research program are also presented.

REFERENCES

[1] Elisabeth Ahlsen, *Introduction to Neurolinguistics*, volume 1, John Benjamins Publishing Company, 1 edn., 2006.

[2] Rabab K Ward Gary E Birch Ali Bashashati, Mehrdad Fatourechi, 'A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals', *Journal of Neural Engineering*, **4**, (2007).

[3] Klaus Robert Muller Benjamin Blankertz, Gabriel Curio, 'Classifying single trial eeg: towards brain computer interfacing', in *Advances in neural information processing systems 14*, volume 1, 1594, (2002).

[4] Wernicke C., 'Der aphasische symptomencomplex', *Braslau: Cohn and Weigert*, (1874).

[5] Honda Kiyoshi Masaki Shinobu Callan Daniel E., Calla Akiko M., 'Single sweep eeg analysis of neural processes underlying perception and production of vowels', *Cognitive brain research*, **10**(1-2), 173–176, (2000).

[6] Kroos Christian Vatikiotis-Bateson Eric Callan Daniel E., Callan Akiko M., 'Multimodal contribution to speech perception reveled by independant component analysis: a single sweep eeg case study', *Cognitive brain research*, **10**(3), 349–353, (2001).

[7] Carin Hertnaes Gert Pfurtscheller Christoph Guger, Werner Harkam. Prosthetic control by an eeg-based brain-computer interface (bci).

[8] Jiankang Wu Cuntai Guan, Manoj Thulasidas, 'High performance p300 speller for brain-computer interface', in *2004 IEEE International Workshop on Biomedical Circuits and Systems*, Institute for Infocomm Research, Singapore, (2004).

[9] Grodd W. Haider H. Kamp H. Mayer J. Riecker A. Wildgruber D. Dogil G, Ackermann H., 'The speaking brain: a tutorial introduction to fmri experiments in production of speech prosody and syntax', *Journal of Neurolinguistics*, **15**(1), 59–90, (2002).

[10] J. L. Bartles J. Brumberg F. H. Guenther P. R. Kennedy L. Miller J. Rebesco A. B. Schwartz S. A. Siebert M. Velliste E. J. Wright, D. S. Andreason. Human cortex long-term recordings [3]: neural net analyses, 2007.

[11] A. Timpen D. Mattia M. G. Martian J. Millan S. Salinan L. Bianchi F. Babiloni F. Cincotti, A. Scipione, 'Comparison of different feature classifiers for brain computer interfaces', in *Proceedings of the 1st International IEEE EMBS*, volume 1, pp. 645 – 647, Capri Island, Italy, (2003). IEEE.

[12] A Lecuyer F Lamarche B Arnaldi F Lotte, M Congedo, 'A review of classification algorithms for eeg-based braincomputer interfaces', *JOURNAL OF NEURAL ENGINEERING*, **4**(2), (2007).

[13] Simon Haykin, *Neural Networks: A Comprehensive Foundation*, volume 1, Prentice Hall, 1 edn., 1999.

[14] Tao Wang He and Bin, 'An efficient rhythmic component expression and weighting synthesis strategy for classifying motor imagery eeg in a braincomputer interface', *Journal of Neural Engineering*, **1**(1), 1–7, (2004).

[15] Salomon Henschen, 'On the function of the right hemisphere of the brain in relation to the left in speech, music and calculation', *Brain*, **49**(1), 110–123, (1926).

[16] Seungjin Choi Hyekyoung Lee, 'Pca-based linear dynamical systems for multichannel eeg classification', in *Neural Information Processing, 2002. ICONIP '02. Proceedings of the 9th International Conference on*, volume 2, pp. 745 – 749. IEEE, (2002).

[17] Seungjin Choi Hye!qung Lee, 'Pca+hmm+svm for eeg pattern classification', *IEEE*, **1**(1), 541– 544, (2003).

[18] Kevin Warwick Ian Daly, Slawomir J. Nasuto. Towards natural human computer interaction in bci, 02/04/2008 2008.

[19] M. Jeannerod, 'Mental imagery in the motor cortex', *Neuropsychologia*, **33**(11), 1419–143, (1995).

[20] Laurence Garey Korbinian Brodmann, *Brodmann's Localisation in the Cerebral Cortex*, Imperial college press, 1999.

[21] Judith McLaughlin Lee Osterhout, Mark Allen, 'Words in the brain: lexical determinants of word-induced brain activity', *Journal of Neurolinguistics*, **15**(1), 171 – 187, (2002).

[22] Steven J. Luck, 'Ten simple rules for designing erp experiments', in *Event-Related Potentials - A methods handbook*, ed., Todd C. Handy, volume 1, 17 – 32, The MIT press, Cambridge, Mass., 1 edn., (2005). Some o these methods seem to be very restrictive to inquiry.

[23] Nicoletta Nicolaou, *Automatic artefact removal from Electroencephalograms*, Phd thesis, Reading, 2006.

[24] Bing Han Patrick Suppes, 'Brain-wave representation of words by superposition of a few sine waves', *PNAS*, **97**(15), 8738–8743, (2000).

[25] Bing Han Patrick Suppes, Zhong-Lin Lu, 'Brain wave recognition of words', *PNAS*, **94**(1), 14965–14969, (1997).

[26] Julie Epelboim Patrick Suppes, Bing Han and Zhong-Lin Lu, 'Invariance between subjects of brain wave representations of language', *PNAS*, **96**(22), 1295312958, (1999). Two of the subjects where not native english speakers.

[27] Julie Epelboim Patrick Suppes, Bing Han and Zhong-Lin Lu, 'Invariance of brain-wave representations of simple visual images and their names', *PNAS*, **96**(25), 14658–14663, (1999).

[28] Zhong-Lin Lu Patrick Suppes, Bing Han, 'Brain-wave recognition of sentences', *PNAS*, **95**(1), 1586115866, (1998).

[29] Broca Paul, 'Perte de la parole', *Bulletin de la Societe d'Anthtopologie de Paris*, **2**, 219–237, (1861).

[30] Jess Bartels Princewill Ehirim Mui Mao Steven Seibert E. Joe Wright Philip Kennedy, Dinal Andreasen. The longevity and stability of multiple neurla signals recorded from human motor speech cortex using the neurotrophic electrode, 2007.

[31] Rappelsberger Peter Schack Baerbel, Weiss Sabine, 'Cerebral information transfer during word processing: where does it occur and how fast is it?', *Human brain mapping*, **19**(1), 18–36, (2003).

[32] Touradj Ebrahimi Karin Diserens Ulrich Hoffmann, Jean-Marc Vesin, 'An effcient p300-based brain-computer interface for disabled subjects', *Journal of Neuroscience methods*, (2007).

[33] Jonathan R. Wolpaw, 'Brain-computer interfaces as new brain output pathways', *The Journal of Physiology*, **579**(3), 613–619, (2007).