KU LEUVEN
FACULTEIT INGENIEURSWETENSCHAPPEN

Linguistic transcription of EEG responses to sequences of visual stimuli

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Thesis voorgedragen tot het behalen
van de graad van Master of Science
in de ingenieurswetenschappen:
computerwetenschappen, eg

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Preface

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Arne Van Den Kerchove

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Abstract

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Acronyms

BCI	Brain Computer Interface
ECG	Electrocardiogram
EEG	Electroencephalogram
ERP	Event Related Potential
N400	Negative ERP component after 400 ms
P300	Positive ERP component after 300 ms
SD	Symbolic Dynamics
SNR	Signal to Noise Ratio

Symbols

Σ	An alphabet of symbols
s_i	A symbol from a given alphabet
w_i	a word, a sequence of symbols
S	a sentence, a sequence of words
D	a dictionary, the set of all words

Chapter 1

Introduction

try to focus on computer science side of things but some neurosciene will be involved ot tackle the problem

Brain Computer Interfaces (BCIs)

what is EEG and BCI? image of EEG

why relevant?

Dear Arne,

On Wednesday 16 October 2019 22:18:20 Arne Van Den Kerchove wrote: > Dear professor Van Hulle, dear Benjamin and Valentina > > > I have some questions regarding the context and the broader relevance of > the research I will be conducting for my thesis about linguistic > transcription of ERP responses. These questions are the following: > > 1. Linguistic transcription seems indeed a good way to uncover possible > sequential structures in series of ERP's. Why exactly is linguistic > transcription the preferred way to do this? The Tupaika paper > shortly mentions that the main reason symbolic transcription is used > is to to capture the nonlinear behavior of the EEG signal but the > techniques used to process this nonlinearity seem rather outdated. > (Symbol Dynamics and Chaotic Dynamics). For starters, individual words are rarely unambiguous, perhaps only when they very concrete, but when placed in a sentence context or discourse their meaning can be resolved. For now, in terms of ERP responses, we usually look at responses to individual words, perhapos when paired with another word, or sentence end-words (cite). It woudl be noce to look at ERP signatures of senetences, whether we can see a context buildup e.g. Also linguistic transcription can uleash lots of other techniques, also those uised in text mining and bioinformatics...

> 3. Am I correct in stating that the main benefits of an algorithm that > can perform linguistic transcription are the following: > * an easier assessment of subject performance in N-Back training This could be a benefit of the transcription but this is not the only thing we are interested in. > * possible expansion to capture sequential context building when > presenting linguistic stimuli Yes. > * the ability to use detected sequential structure in ERPs as a > predictor for future ERPs Yes. > * possibility to semantically correlate the transcribed > symbols/words to the shown stimulus Euh this is a bit too ambituous but perhaps we can distinguish abstract

from concrete words. > * Automatically annotate an EEG with waveform types (the waveforms > corresponding to the words/symbols learned) which would allow > for automatic detection of certain patterns or easy expert > interpretation (e.g. detecting of types of epileptic waveforms) Yes. > > > I also want to inform you that the first presentation and discussion > with professor Blockeel about the problem statement, the relevance of > the research and the initial plan will take place on Friday, October > 25th, 9:45h at Campus Arenberg, 200A 01.112 (RUBY room). You are all > invited to join this presentation and discussion. Noted.

Best,

Marc > > > Kind regards > Arne Van Den Kerchove > r0579667

Chapter 2

Problem Statement

The goal of this thesis is to develop an algorithm to uncover sequential structure in EEG signals. The algorithm will transform an EEG signal to a sequence of symbols. These symbols can be regarded as the basic elements of a language, hence the title *linguistic transcription* (section 2.1). After transcription, the symbols can be grouped together to form words that become part of a dictionary. The constructed dictionary can be used to describe the transcribed EEG. This representation allows other algorithms to analyze and exploit possible sequential information in the EEG traces.

In practice, the algorithm will be implemented for EEG's recorded while presenting test subjects with visual stimuli. These stimuli elicit so called Event Related Potentials (ERPs) (section 2.2) when shown. ERPs are peaks in EEG activity that appear within a short, fixed period after a sensory event (the stimulus). The algorithm will be applied to the EEG responses acquired during N-Back training in test subjects. N-Back (section 2.3) is a visual paradigm in which images are presented to the test subject at fixed intervals while recording an EEG. N-Back produces a sequence of ERPs, time-locked to the stimuli, that can be transcribed by the algorithm. Finally, the technique of spatiotemporal beamforming (section 2.4) will be used to cope with the low signal to noise ratio of the EEG.

2.1 Linguistic transcription

The task of the Linguistic Transcription Algorithm is to construct a sentence of words describing a given EEG. When performing the N-Back task described below, the brain consistently produces ERPs. These ERPs can be clustered together based on similarity. Each cluster can than be assigned a symbol to represent examples of that cluster. This is the core idea of the algorithm. New, unseen ERPs are then assigned the symbol of the cluster they are closest to.

Definition 1 *A* ***symbol*** $s_i \in \Sigma$ *is a token from alphabet* Σ *representing the centroid of a cluster of ERPs. Symbols can be used to describe an example of an ERP that belongs to the corresponding cluster, or to describe the cluster itself. Throughout this thesis, symbols will be represented by alphabetical characters.*

After a sequence of ERPs has been transcribed into a sequence of symbols, these symbols can be grouped together to form a word.

Definition 2 *A **word** $w = \{s_x, s_y, s_z, ...\}$ is a sequence of symbols, representing a short sequence of ERPs that might reflect a specific relation between the transcribed ERPs. Word limits can be chosen in correspondence to the nature of the stimuli.*

Definition 3 *A **sentence** $S = \{w_x, w_y, w_z, ...\}$ is a sequence of words.*

Definition 4 *A **dictionary** D is the set of all encountered words.*

Hence, an example of a transcribed sentence could `ABCD BAAA ABCD AAAABCD`.

This linguistic transcription allows for easy sequential analysis, both manually and automatically. Experts and algorithms can easily detect structures in the transcribed words (for instance, notice the frequent occurence of `BC` before `C` in the transcribed sentence above).

One important reason the linguistic transcription is chosen as a tool to uncover sequential structure is the fact that it can easily capture recurring patterns in words. This is most interesting when applied to linguistic stimuli. This is the case in BCI paradigms where words (actual words, not to confuse with with transcribed words from Definition 2). Instead of analyzing the ERP response to single words in a presented sentence [4], analysis can now be done on the entirety of the presented sentence. The transcription could then directly reflect semantic and lexical concepts such as context build up. When all words are aggregated in a dictionary, statistical analysis can be carried out to reflect on the distribution of words an patterns.

Another study [25] claims symbolic transcription is necessary for EEG analysis with Symbolic Dynamics [23], which is a technique that allows for EEG analysis without loss of nonlinear information present in the EEG [1]. This is not the main focus of this thesis.

2.2 BCI and ERPs

In Brain Computer Interfaces (BCI), a common technique used to measure brain activity is the Event Related Potential (ERP). ERPs are peaks in the EEG that are time-locked to a specific stimulus and usually appear within 1 second after the first stimulus. ERPs are easily detectable and extensive research has shown that they can carry semantical and contextual information about the presented visual and auditory stimuli [2, 4, 7, 8, 13].

In general, however, ERPs have a very low signal to noise ratio (SNR). To cope with this problem, similar stimulus trials are often repeated and averaged together to extract the ERP [17]. Because this thesis is interested in individual ERP responses and their context (surrounding ERPs), averaging cannot always be applied here. It is after all possible that when a stimulus sequence is repeated, its context has changed. To cope with this inherently low signal to noise ratio, the spatiotemporal beamformer (2.4) will be applied.

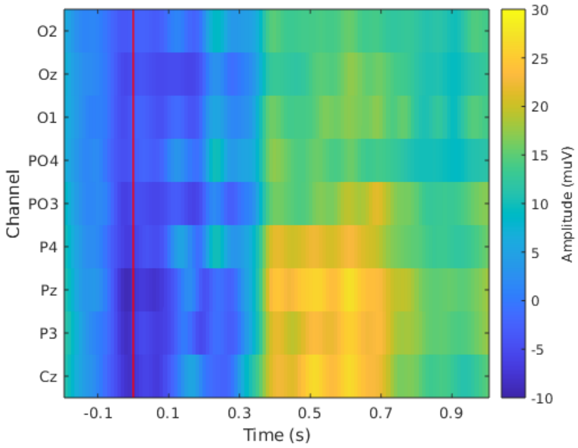

FIGURE 2.1: Spatio-temporal ERP represenation example for multiple channels. The P300 component occurs later than expected with a maximum amplitude around 600ms.

An ERP can consist of multiple components with a fixed naming scheme. For instance, when the ERP shows a positive deflection 300ms after the stimulus onset, this is denoted as the P300 component (P=positive). Research has shown that different components carry information about different brain processes involved in processing the stimulus. Of specific interest for the linguistig transcription of the *N*-Back paradigm are The P300 component, which is related to the working memory [3] and the N400 component, which can express semantic information about the stimulus [16].

image showing ERP components

2.3 *N*-Back Paradigm

The *N*-Back task was introduced in multiple variants by Kirchner in 1958 [12] and by Mackworth in 1959 [18], initially as a working memory training task. It was later introduced in neuroscience and EEG studies by Gevins et al. [6]. In the *N*-Back task, stimuli are shown to a test subject for a short time at fixed intervals. The subject is asked to press a button if the a stimulus matches another stimulus, shown N intervals back, with N a fixed number for the task. In that case, the last shown stimulus is denoted as a *target* stimulus. An example is shown in Figure 2.2. Common *N*-Back levels used are *1-back*, *2-back* and *3-back*. *0-back* is sometimes used as a baseline or for validation.

The *N*-Back BCI paradigm is chosen for the initial development of the Linguistic Transcription Algorithm because a concrete hypothesis can be attached to the transcribed results:

Hypothesis 1 *Does the fact whether the current stimulus is a target stimulus or not affect the processing of future stimuli in the brain?*

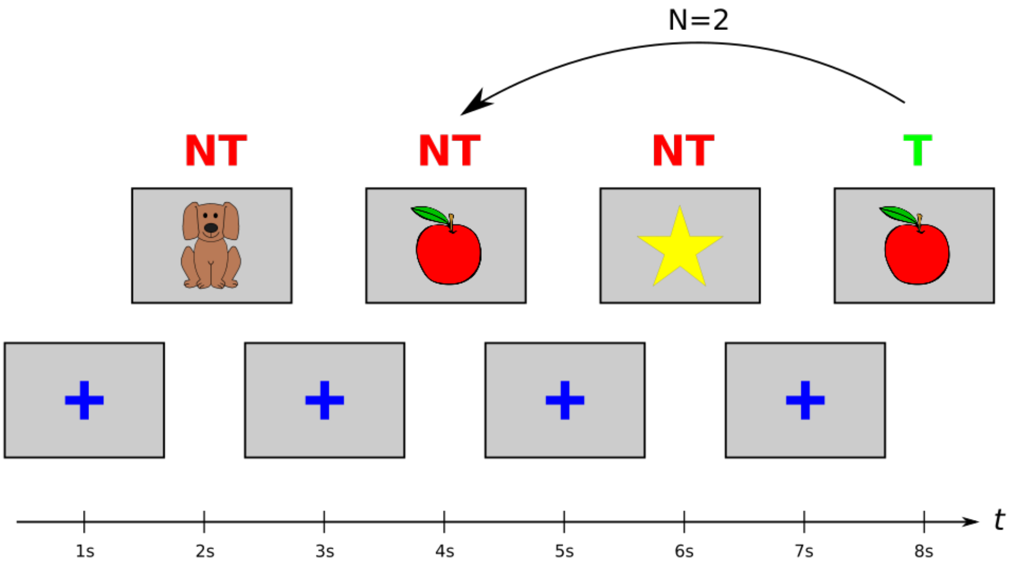

Figure 2.2: Graphical rendition of a visual *2-back* task with one target (T) and several non-targets (NT)

.

An additional advantage is the availability of N-back EEG data, gathered for research about transfer effects of N-back training to other cognitive tasks by Pergher et al. [21, 22].

The specific N-Back tasks used in this research are visual *1-back*, *2-back* and *3-back* tasks as defined by Pergher et al. [21]. On a screen, stimulus pictures are shown for a duration of 1000ms, followed by a 2000ms inter-stimulus interval. In this interval, the subject is asked to focus on a fixation cross in the center of the screen. The shown pictures consist of easy recognizable objects (e.g. a dog, an apple, ...).

Each time a target or non-target stimulus is shown, an ERP is elicited in the test subject. Studies regarding the N-Back paradigm often focus on the P300 component of the ERP. Several studies have shown that the complexity of the task, the information transmitted to the subject and the level of training of the subject can influence the amplitude [9, 10, 13–15, 19] and latency [5, 24]of the P300 potential in the N-Back task and similar tasks such as the Sternberg task. The general morphology of the P300 ERP component has been studied by Watter et al. [27]. It is clear that the P300 ERP component an N-Back trial encodes useful and easily distinguishable information for the algorithm to transcribe. While it might provide a useful tool for a preliminary study, the final algorithm will have to take the entirety of the ERP waveform into account to exploit possible other present information (for instance semantical information in the N400 component).

2.4 Spatiotemporal Beamformer

In literature study?

can be used to extract features for clustering when activation pattern is decided can be used as classifier after constructing dictionary

2.5 Transcription procedure

image of transcription procedure

Chapter 3

Literature Review

In the past, there have been few attempts at crafting a linguistic description from an EEG signal. Most of the research that actually constructs a sequence of symbols from the EEG focuses on symbol dynamics or direct annotation of the signal (section 3.1), which is not directly applicable to a given set of ERPs. In a more broad sense, the problem statement can be interpreted in finding a clustering of time series subsequences with a dictionary of cluster centroid ERPs as a result. For this purpose, more researched signal processing techniques such as Dictionary Learning (section 3.2) and Time-series Motif Discovery (section 3.3) are also reviewed. Finally, as it will become clear that these techniques are insufficient for the purpose of this thesis, the concept of the Spatio-temporal Beamformer is introduced to cope with some problems.

3.1 Symbolic Dynamics and Rapid Annotation

Several studies have transcribed the EEG signal to a sequence of symbols for analysis with Symbolic Dynamics. The most notable one is described in a 2010 paper by Tupaika et al. [25], while some other applications are described in [11, 20]. Symbolic dynamics (SD) is a rather mathematical technique to model non-linear chaotic systems as a space of sequences of abstract symbols and a shift operator [23]. The idea stems from an earlier successful application of symbolic dynamics to construct a classifier for the ECG [26]. When applying SD, results achieved with ECG data are generally better than for EEG data because of the lower complexity of the ECG signal.

Given an EEG signal

$$X = \{x^{EEG}\}_{i=0,1,\ldots} x \in \mathbb{R}$$

SD constructs a sequence of symbols by thresholding the signal at different levels. To calculate a corresponding transcribed sequence W, the following function is applied:

$$s_n = \begin{cases} a & \text{if } \mu < x_i \leq (1-a)\mu \\ b & \text{if } (1+a)\mu < x_i < \infty \\ c & \text{if } (1-a)\mu < x_i \leq \mu \\ d & \text{if } 0 < x_i \leq (1-a)\mu \end{cases} \in \Sigma_{SD} \tag{3.1}$$

$$W = \{s_1, s_2, ...\} \tag{3.2}$$

image of thresholding and bins

with μ the mean of the EEG signal. The equation shows that, in contrary to the problem statement of this thesis, the SD algorithm directly translates each data point to a symbol. It might however be possible to apply this method to entire ERPs, which consist of multiple subsequent EEG data points, or to translate each ERP to multiple symbols by manipulating sample rates. Another issue is the fixed size of the alphabet. In the example above, the alphabet Σ_{SD} contains only 4 symbols. If the goal is for a word to reflect sequential structures in the ERPs, this is very restrictive. It might be possible that more symbols are needed to represent the required information. A data-driven solution to determine the number of symbols would better be able to cope with this problem. Finally, thresholding the amplitude of the EEG signal on a priori fixed intervals is a relatively simple technique that might be apt for SD analysis, but would probably not result in an informative sequence for other analysis techniques. While the transcription method of the SD approach is not applicable to the ERP transcription in this thesis, it does provide useful insights in analysis methods for a transcribed sequence.

pros: word analysis, entropy measures, find out if SD classification can be used with our alg

durand, Jing: pros: cutting of erps in components, features in jing and Rodriguez-Sotelo2012

time series clustering

3.2 Dictionary learning

dictionary learning shows a formal shows a formal shows a shows a formal shows a formal formal

3.3 Motif discovery

westover why not good for ERPs? SNR

different paths: directly transcribe signal peaks (threshold: tupaika, cluster: Jing, durand); motif discovery (westover) (not applicable SNR); classify beamformer output; dictionary learning

3.4 Spatio-temporal beamforming

Chapter 4

Conclusion

De masterproeftekst wordt afgesloten met een hoofdstuk waarin alle besluiten nog eens samengevat worden. Dit is ook de plaats voor suggesties naar het verder gebruik van de resultaten, zowel industri"ele toepassingen als verder onderzoek.

Appendices

Appendix A

Appendix A

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Fiche masterproef

Student: Arne Van Den Kerchove

Titel: Linguistic transcription of EEG responses to sequences of visual stimuli

Nederlandse titel: Symbolische transcriptie van EEG responses op snelle sequenties van beelden

UDC: 621.3

Korte inhoud:

Hier komt een heel bondig abstract van hooguit 500 woorden. LaTeX commando's mogen hier gebruikt worden. Blanco lijnen (of het commando `\par`) zijn wel niet toegelaten!

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Thesis voorgedragen tot het behalen van de graad van Master of Science in de ingenieurswetenschappen: computerwetenschappen, eg

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