# EEG analysis methods in neurolinguistics: a short review

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**The quantitative analysis of neurolinguistics tasks requires complex measurement and evaluation methods. Due to the interdisciplinary nature of these research tasks, the cooperation of medical, engineer and linguistic experts is necessary. This paper presents the most prevalent EEG analysis methods, from simple to complex, that can help us in understanding the neural basis of language processing. Our research group works in collaboration with the Hungarian and Applied Linguistics Institute of the University of Pannonia and the Department of Physiology of the University of Szeged.**

***A neurolingvisztikai problémák (kvázi-részletes) kvantitatív vizsgálata egyre bonyolultabb mérési és mérés-értelmezési feladatok megoldását/bevezetését igényli. Értelemszerűen a kutatás igényli az intenzív orvos-mérnök kooperációt. Jelen dolgozat igyekszik logikus csoportosításban eljutni a korai próbálkozásoktól a ma leghatékonyabbnak tekinthető módszerek bemutatásáig, hivatkozva a releváns irodalomra. Biomérnöki kutatócsoportunk az orvosi-nyelvészeti kérdésekben a Pannon Egyetem Magyar és Alkalmazott Nyelvtudományi Intézetére, ill. a Szegedi Tudományegyetem Élettani Intézetére támaszkodik.***

## INTRODUCTION

Understanding how our brain recognises and understands languages, extracts syntactic and semantic information is one of the grand challenges of science. Theoretical linguists have proposed various models for word and sentence recognition [1] that psycholinguistics aims to verify with targeted cognitive experiments. A long-time tool for proving hypotheses in psycholinguistics is reaction time analysis [2], which while provides a simple yet powerful method for researchers, lacks the ability to discover the fine intrinsic details of task execution. The rapid development in electroencephalography (EEG) and functional MRI (fMRI) technology over the past two decades have catalysed research in neurolinguistics, whose goal is to discover and understand the neural mechanisms underlying language processing. While current fMRI devices can produce images with 1 mm$^3$ spatial resolution, they lack the temporal resolution necessary for the exploration of sub-second cognitive processes. EEG, on the other hand, has the required sub-millisecond temporal resolution but it has limited spatial resolution. Our group focuses on high-density EEG imaging and develops methods that can increase the spatial resolution of EEG. A recent collaboration enabled us to start examining the benefits of EEG imaging in linguistics. The focus of this research is on language localisation, understanding the mechanisms of using multiple languages and the neural organization of language processing of bilingual speakers.

The number of EEG analysis methods available for neurolinguists can be overwhelming. The purpose of this paper hence is to review the most important methods that can be used effectively in the analysis of bilingual language processing tasks. After a brief introduction to the fundamentals of EEG technology and neurolinguistics, analysis methods in their order of complexity are described. We look at Event Related Potentials and their analysis methods, then we focus on time-frequency analysis of measurements. In the last section we overview methods for discovering the connectivity patterns of different cortical areas during the execution of a language task. Finally, we conclude the paper with an outlook for our research and the set of methods we selected for the next stages of our work.

## FUNDAMENTALS OF EEG TECHNOLOGY

EEG is a non-invasive method to measure the bioelectric activity of the brain using electrodes placed on the scalp. The source of the activity is the change in the post-synaptic potentials of cortical neurons acting as tiny current generators placed in a direction perpendicular to the cortical surface. When a sufficiently large population of nearby neurons is activated simultaneously, the generated current fluctuations cause detectable changes in the electrical field of the brain [3]. The scalp potential distribution, generated by this electric field, can be measured by a suitable EEG measurement device and a set of scalp electrodes, and can be stored in a computer for later processing and analysis. The number and layout of the electrodes used in practice can vary greatly, but high-density 64 or 128-electrode systems arranged in the universal 10/10 or 10/5 layout [4] are the most common in research laboratories.

The main advantage of EEG over other brain imaging methods (e.g. fMRI, PET) is its superior temporal resolution. Typical EEG sampling rates are in the range of 512 to 4096 Hz, which enable us to follow the time course of brain activity at millisecond or sub-millisecond resolution. Unfortunately, EEG has low spatial resolution. The head is made up of tissues (white and grey matter, cerebrospinal fluid, skull, scalp) with varying conductivity properties. When the generated current flows from the cortex to the scalp, it must pass through the skull which has a relatively low conductivity (high resistivity). As a result, the current spreads out laterally within the skull instead of passing straight through to the scalp. The result of this so-called volume conduction effect is the reduced spatial resolution and the 'smeared' or 'blurred' appearance of activation sources on the scalp potential distribution image.

## NEUROLINGUISTICS AND BILINGUALISM

The main focus of neurolinguistics is the understanding of language processing by uncovering its underlying neural mechanisms. Researchers typically use neural imaging methods (in general EEG and fMRI) to detect activity patterns during various language-processing tasks. The key research topics include, among others, the localisation of language processing, analysis of the time course of processing as well as the neural mechanisms of language acquisition. It is known that there are special areas dedicated to language processing, such as the Broca and Wernicke areas [5], but recent theoretical and experimental findings suggest that language processing is performed by a dynamic, distributed network of cooperating neural sources [6], [7]. Another increasingly important research area is second language acquisition, i.e., understanding the underlying mechanisms of learning and using multiple languages. Neurolinguistics can help in discovering differences between the monolingual and bilingual brains, and the findings might help in developing more efficient foreign language teaching methods for our children. Much is known about the localisation of word and sentence processing, but more bilingual experiments are needed that can verify the location, overlap and temporal properties of first (L1) and second (L2) language processing, and test the validity of theoretical bilingual language processing models [8]. Due to the speed of these cognitive processes, only EEG can provide the necessary temporal resolution for examining these issues. In the following sections we overview and discuss various analysis methods that can help in answering the above research questions.

## EVENT RELATED POTENTIAL ANALYSIS

The amplitude of the EEG signal measured on the scalp is normally within the range of ± 50 $\mu$V. The biologically meaningful small-amplitude signal is usually embedded in relatively high level of noise generated by various biophysical sources (muscle activity, ECG, eye movement, blinks), skin resistance changes, electrode malfunction, and so on, making the detection of small amplitude changes difficult (e.g. Figure 1). A well-established method for this problem is signal averaging. Assuming that noise is a random process with zero mean, the sample-wise averaging of a sufficiently large number (>100) of EEG trials (time window of task of interest) in a stimulus-synchronised manner will cancel out noise and leave only the stimulus-locked components in the resulting signal, as shown in Fig 1. Successful averaging requires very precise synchronisation of the datasets of the repeated experiments, therefore stimulus presentation and response triggers are used to mark the start and end of the experiment trials. Depending on which trigger is used for averaging, we can distinguish between stimulus or response-locked averaging. The resulting trigger-based average potentials are called event-related potentials (ERP). Depending on the applied stimulus type, we can examine visual, auditory, sensory and other cognitive tasks with this method.

The execution of cognitive tasks involves various sensory, cognitive and motor processes. The sum of these processes appears in the averaged ERP waveforms in the form of components. Components are distinct positive or negative potential peaks, as illustrated in Fig. 2, named by the polarity (negative/positive) and the order or time stamp of the peak, e.g. N1, N2, P1, etc.  or N100, P300 or P500. The analysis of these waveforms allows us to compare ERPs obtained under different conditions and consequently test scientific hypotheses.

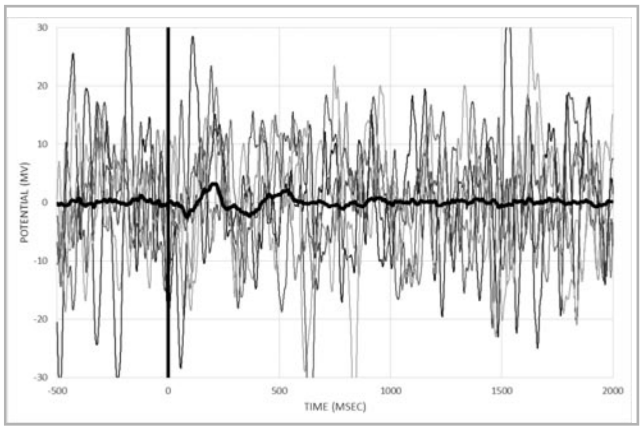


***Figure 1***
***Averaging individual trial EEG measurements (thin grey lines) to increase signal-to-noise ratio and create ERP waveform (thick black line). Vertical line at t=0 represents stimulus presentation time.***

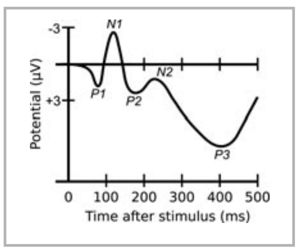


***Figure 2***
***Typical ERP components: positive and negative peaks designated by their order P1, P2, P3 or the time they appear, e.g. P100, N400. ERP is often displayed with reversed polarity showing negative peaks pointing upwards. (Source: https://en.wikipedia.org/wiki/Event-related_potential)***

Before averaging, pre-processing steps must be carried in order to improve ERP quality. Signals are typically filtered by a zero-phase 0.5-45 Hz band-pass filter. Then, trials that include signals with extreme large amplitudes, large DC shifts, or contain bad electrodes or eye movement artefacts are rejected from averaging. Sophisticated statistical artefact removal methods are also available if we wish to keep the number of rejected trials to the minimum [9], [10]. Components can be characterised by several metrics, such as peak latency, peak amplitude and peak onset [11]. These values can be used in subsequent statistical analyses for detecting significant statistical differences between ERP data, e.g. when comparing P300 peak amplitudes. Note, however, that peak amplitude and latency are rather unreliable metrics as they are the result of averaging. Depending on the phase-locking properties of the components in the individual trials, large variance (component jitter) will result in reduced peak amplitude and a shift in peak latency. A more reliable approach minimising the effect of latency jitter and peak fluctuations is to compare the mean amplitude values or the area under curve within the specified time interval of interest.

## COMPONENTS AND LINGUISTICS

ERP has been used extensively in linguistics experiments for decades and several characteristic components have been identified that describe specific neural properties of language-related task execution [8]. Mismatch negativity (MMN) is a component that occurs during auditory sensory experiments when an infrequent sound, deviant from the frequently presented standard sound, is heard by the subject. MMN can be used successfully in speech perception experiments as it is a pronounced negative amplitude increase at 100-200 ms after the onset, detectable around the primary auditory and frontal cortical areas. The N170 and P200 components are identified as visual orthographic processing indicators detectable on the occipital lobe. The P300 component is a strong positive peak believed to reflect the effort of using working memory (especially in decoding of pseudowords or non-familiar words). The N320 component is associated with phonological processing and phonological decoding tasks. The N400 component is connected to semantic processing of sentences. If a semantically incorrect word is presented in a sentence, a strong negative component appears in the temporal area between 300 and 500 ms after the stimulus onset. It is believed to represent the increased difficulty of semantically integrating the word with the context of the sentence. The rise of the P600 component is linked to syntactic processing and memory decisions during word and sentence processing.

The above components can be used successfully in the study of bilingual language processing tasks [12], [13], [14], [15]. As shown by Moreno et al. [16], MNN can be used to examine phoneme discrimination for different languages in young infants, or in adults learning a second language, while N400 can be used to investigate sentence processing at the semantic level. One of the most interesting questions in bilingual language usage is the control of the two languages. The N200 component (right frontal areas) when using the Go/noGo paradigm can help detect interference of a language during a lexical decision task. It has also been shown that ERP components of bilingual subjects are modulated by the age of language acquisition as well as the level of language proficiency.

## TIME-FREQUENCY ANALYSIS

EEG produces non-stationary signals having distinct spectral and phase properties. It is known that the brain produces neural oscillations at different frequency bands in different mental states [17]. These oscillations, sometimes called brain waves, can be easily detected e.g. using band-pass filters. The best-known brain frequency band, alpha (7.5–12.5 Hz), represents relaxed, resting-state activity. Conscious, planned task execution produces oscillations typically in the beta (13–30 Hz) and gamma bands (low gamma: 30–70 Hz, high gamma: 70–150 Hz). Other frequency bands, such as delta (1–4 Hz), theta (4–8 Hz) normally appear in childhood and/or different sleep stages.

Unfortunately, traditional ERP analysis cannot detect activities nor oscillations in specific frequency bands or provide information of the phase of the events. Time-frequency analysis provides techniques that help uncover this information from the EEG signals using various signal processing techniques. The main advantage of this type of analysis is that it reveals more (especially task-related) details than averaging-based ERP, produces results that can be interpreted in terms of neural oscillations, and acts as a bridge linking different fields of neuroscience. The traditional tool for time-frequency analysis is the Fourier transform, which decomposes periodic, stationary, time-invariant signals into a number of sinusoid components. EEG signals, however, are neither time-invariant nor stationary signals, therefore the Fourier transform in its original form is not applicable. Early analysis methods were based on a modified version of the Fourier transform, the Short-Time Fourier Transform, which decomposes the original signal to its components only within a time window [18]. The width of the window is used to fine-tune the temporal vs spectral resolution of the method. A more advanced and accurate analysis method is based on the applications of wavelets (multi-resolution basis functions). In the EEG literature, the Morlet continuous wavelet is the most popular method, as it can produce high spectral and temporal resolution time-frequency images [19], [20]. Wavelet analysis enables us to extract signal power, phase and coherence as a function of time and frequency, and examine alpha, beta or gamma activity separately (see Fig. 3). Phase differences can also be easily identified and used to describe stimulus-locked or induced oscillations at specific frequencies [20].

Since time-frequency analysis is a relatively new technique and requires more advanced signal processing methods, its use in linguistic experiments is not widespread. In [21] Lewis et al. examined the role of beta and gamma oscillations in language comprehension at the sentence processing and found that gamma oscillations represent lexical prediction effects during sentence understanding. Grabner et al. [22] used time-frequency analysis methods for obtaining a more accurate model of language translation mechanisms. They found that parietal event-related synchronisation occurred in the theta band (increase in theta oscillation power) whereas alpha band de-synchronization (decrease in power) was measured in the left hemispheric cortical areas. These finding indicate a connection between theta/alpha band activity and lexical/semantic processes during translation. Wang et al. [23] compared the word processing process of bilingual and monolingual speakers. Although the measurement technique uses is magnetoencephalography (MEG), the analysis methods are identical to EEG. They found that most regions active during word processing show both beta and gamma band oscillations and power increase, but these power increase is greater for the bilingual speakers at the left language areas. Correira et al. [24] used multi-parameter pattern analysis (MVPA) method to decode a spoken word from the subject's EEG recording. Weiss et al. [25] investigated coherency in language processing experiment. High synchronization has been found between two electrodes located in left frontal and Broca areas in the alpha band 8-10 Hz.

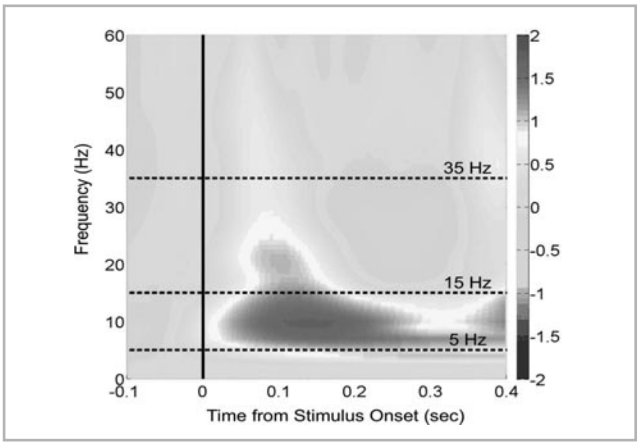


***Figure 3***
***Time-frequency diagram of an ERP showing a long activation period in (20-300 ms) the alpha (10 Hz) band and a short activation peak at 100 ms in the beta band (15-35 Hz).***

## CONNECTIVITY ANALYSIS

ERP and time-frequency analysis methods can be used to verify hypothesis based on various experimental conditions and to explore the temporal/spectral/spatial characteristics of the EEG data. They do not, however, provide information about the nature and operation mechanisms of the distributed cortical networks underlying the given cognitive processes. Language processing, as stated earlier, is generally viewed as a distributed mechanism, backed by a complex cortical network [7]. Connectivity analysis – the collections of methods for investigating the interconnection of different areas of the brain – provides the theoretical basis as well as the practical tools describing the operation of these networks [26].

Different areas of the brain are connected by neural fibres or tracts of the white matter, transmitting information between distant brain regions. This type of connectivity, the Structural Connectivity, describes the anatomical connections in the brain. Diffusion Tensor Imaging [27] can be used to detect anatomical fibres and construct structural networks. Structural connectivity, however, presents a rather static and limited view of the brain; it cannot fully describe the short-range, dynamic and plastic interconnection and activation mechanisms found in brain processes. Functional and Effective Connectivity networks provide this crucial additional information for us [28]. Functional Connectivity describes the temporal correlations in activity between pairs of brain regions. The connectivity may reflect linear or nonlinear interactions but it ignores the direction of the connection. Effective Connectivity, on the other hand, uses measures that enable it to describe causal influences of one region on another, hence explore dependencies in our network.

Connectivity is described by networks, which are in fact graphs, consisting of nodes (brain regions) and edges (connections) [29]. Nodes ideally should represent coherent structural or functional brain regions without spatial overlap. EEG measurements can be problematic in this sense, since EEG electrode locations may not be aligned with the boundaries of regions. In addition, because of volume conduction, electrodes may detect spatially overlapping signals. One solution to the latter problem is to compute functional connectivity networks on the cortex instead of the scalp using spatial deconvolution [30]. Links represent anatomical, functional, or effective connections (link type) but can also have weight and direction associated with them. Binary links only represent the presence or absence of a connection. Weighted links, on the other hand, can represent various properties. In anatomical networks, weights may represent the size, density, or coherence of anatomical tracts, while weights in functional and effective networks may represent respective magnitudes of correlational or causal interactions. In functional and effective connectivity networks, links with low weights may represent spurious connections that obscure the topology of strong connections. These can be filtered out using suitable thresholding policies.

To use these constructed networks in a quantitative manner, network measures are needed [29]. Measures can characterise the properties of local or global connections in the network, detect various aspects of functional integration and segregation, or quantify importance of individual brain regions. Measures exist at the individual element level or globally

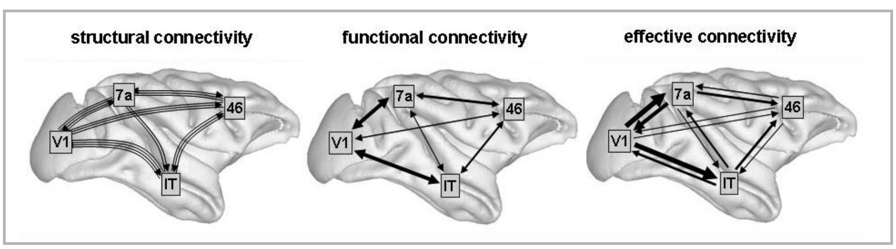


***Figure 4***
***Varying information content extracted by different connectivity analysis methods. (Source: http://www.scholarpedia.org/article/Brain_connectivity)***

as distributions of individual measures. The degree of a node is the number of its links, i.e. the number of its neighbours, representing the importance of a node. The degrees of all nodes create a degree distribution which is important to describe e.g. the resilience of the network. The mean of this distribution gives the density of the network. Other measures, e.g. the number of triangles in the network, or the number of triangles around a given node (clustering coefficient) describe the level of functional segregation – the presence of functional groups/clusters – in the network. Path length and average shortest path length provide information about the ability of the network to combine information quickly from distant brain regions. Further specific measures can be found in [29].

Connectivity is a relatively young area in neuroscience and neuroimaging. Its use in linguistic studies is rather rare. Results from fMRI-based connectivity studies show that in the linguistic domain, the effective connectivity networks are the most useful structures for exploring the spatio-temporal characteristics of word and sentence understanding tasks [31,32].

## CONCLUSIONS

In this paper, we presented a short overview of the various analysis methods one can use in evaluating EEG measurements. Averaged event related potential (ERP) waveform analysis is preferable if the goal of the study is to verify hypotheses by cognitive experiments. The advantages of ERP are that it is a simple, easy-to-compute method that requires very few parameters. It has high temporal resolution and accuracy, its literature is vast, the evaluation methods are well established, documented and supported by many EEG processing software packages. The disadvantages of ERP are due to averaging: null results can occur if averaging cancels out significant components due to extensive component jitter and, similarly, some temporal detail and accuracy is lost in averaging. It does not provide easily interpretable information about spectral characteristics and it can be difficult to link the results with underlying physiological mechanisms (e.g. inter-regional synchronisation or cross-frequency coupling).

Time-frequency analysis methods provide a more advanced set of tools that provide information of activity in different frequency bands and lend themselves naturally to the examination of oscillations and phase properties of the given cognitive process. It allows us to better separate the components of a task that contain perceptual, cognitive and decision subtasks. Time-frequency analysis results also more naturally connect with neural mechanisms at lower spatial scales. The limitation of the method is that it uses more complex and sophisticated theoretical methods and increases the number of parameters in the models, which further complicates subsequent statistical analyses. It also loses in temporal resolution (although still better than that of fMRI) and finally, hypothesis driven research is more difficult to conduct as there are fewer reported findings in the literature relating time-frequency results to cognitive processes.

Different types of connectivity structures can be constructed to show the anatomical, functional and causal connections between brain regions. While structural connectivity can be used to describe the anatomical fibre tracts, and as such can be useful in identifying neural degenerations, functional connectivity can be used with more success in exploratory linguistic studies to discover correlations and significant differences in semantic processing under different conditions. Effective connectivity is considered a pivotal tool for estimating the dynamic connectome changes in bilinguals, which describes the directed temporal coherence between different regions and provides a de-facto circuit diagram of regions participating in the execution of linguistic tasks.

The next stage of our research will include systematic time-frequency analysis of high-resolution EEG measurements to identify spectral components of bilingual language processing, as well as effective connectivity studies in order to examine neural networks and their execution mechanism reported in fMRI studies. Our long-term goal is to create an EEG based imaging methodology that is more accurate and less expensive than fMRI experiments and consequently can be used in routinely in cognitive research.

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