

Methods of Electroencephalography in Neurolinguistics: A Systematic Review

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Abstract—More recent studies conducted on EEG-based brain-computer interaction, that record electrical currents in the brain that arise when a person learn second language in one of that forms (overt speaking, or imaginary speaking, or spoken listening). Brain signals can be obtained and analyzed using a variety of methods as described in this review. Specifically, EEG signals can be analyzed by using several of methods. Some studies dealt with linguistic brain disorders as they focused on language areas such as Broca's aphasia, Frenka aphasia, and others, all of which were on previously acquired languages without addressing the impact of linguistic brain disorders on learning and acquiring other languages. Our main goal here is to review all currently available methods to monitor and know the effect overt when learn new language involving EEG measurements of effects on human brain.

Index Terms— BCI, Electroencephalography, Neurolinguistics, Overt Speech, Second Language, ERP.

I. INTRODUCTION

Electroencephalography or in short (EEG) is the mechanism of placing electrodes on the scalp to detect or monitor the electrical activity of the brain, where It senses and records electrical waves that emit from hundreds of millions of neurons make up the human brain. EEG is a natural impression of the state and capacity of the mind and has the attributes of being unpredictable, time-differing, and unstable. Simultaneously, the brain is moreover a significant organ of the human body, which has noteworthy research regard. Exploring EEG signals and its work helps in many areas the most important of which are medical diagnostics. It also provides a good understanding and knowledge of many scientific researches interested in the cognitive or functional aspect of the brain; many of studies have proposed the non-invasive brain computer interface (BCI) technology depending on EEG (Angrisani, 2017; Nicolas-Alonso & Gomez-Gil, 2012; Ramoser, 2000). The researchers resort to using machine learning methods to classification and recognition the EEG signals after they have extracted the Features of these signals. The ultimate goal is understand how brain works and to control external device by send instructions and for the comprehension and explanation of the neural bases for language knowledge and use. Recently become the frequency domain and time domain analysis is the most used methods to processing of EEG signal such as Fast Fourier Transform (FFT). The next stage for signal processing is using machine learning methods such as SVM (support vector machine), ANN (artificial neural network) and other techniques to classify EEG signals (Shi & Lu, 2009; Mounjou et al., 2015; Mounjou et al., 2016; Mandeep et al., 2012).

There are many studies related to Electroencephalography (EEG) to try to understand and know the various brain functions whether in diseases or unsatisfactory situations and from these studies neurological linguistics, including what is related to the place to store and understand languages or related of brain diseases such as Alzheimer's, dementia, epilepsy and aging on the storage and understanding of languages in the brain. However, studies related to learning foreign languages on the brain in terms of storage capacity, brain functional perceptions or measuring the amount of intelligence and understanding compared to effects monolingual (negative or positive) on the brain when learning a second or more languages are still few and in their initial stages.

II. COMMON EEG PATTERNS

The human cerebrum is the most complex part in the human body; it consists of billions of neurons interconnected to produce an electrical or magnetic activity that varies from person to person depending on the type of activity performed. There are many non-invasive and also invasive techniques for mapping brain signals such as: Functional Magnetic Resonance Imaging (fMRI), Magneto Encephalography(MEG), Near-infrared Spectroscopy(NIRS), Electroencephalogram(EEG), Event related optical signal (EROS), Positron Emission Tomography (PET). Among all the non-obtrusive strategies for analyzing human cerebrum, the direct measure by Electroencephalography of cortical activity that is provided the best temporal resolution with less than milliseconds. One of the main advantages of using EEG technology is its ability to extract brain signal features without stimuli (Lakshmi et al., 2014; Bhise et al., 2020; Ruiz et al., 2017). Some software and tools are available that used for analysis and visualization of neuron images with aim understand and monitoring the structure and function of the brain, here focus only on neuroimaging software tools used by EEG such as EEGNET, Human Neocortical Neurosolver, Neural Ideal, NEURON, Autopatcher, NUTMEG, NetPyNE, nelpy and...etc (Umr & Université).

III. LANGUAGE ACQUISITION

When learning a new language, the age of the language learner is very important. There are many studies that show the importance of age in language learning, and how it improves its acquisition and mastery in early stages. Communication through language is one of the main capabilities that distinguish humans from animals. The human brain is commonly considered the nexus for language acquisition (Kuhl, 2010). However, the process of how language is acquired has been the subject of intense debate throughout the history of science, and as a result, there have been many scientific investigations to understand the formation of language in the brain. Language acquisition theorists can roughly be divided into two main camps of behaviorists (also known as empiricists) and nativists, who argue for learned language and innate language skills, respectively (Spelke, 1998; Binder & Smith, 2013).

Behaviourists propose that the formation of language is the result of interaction with the environment through stimulus-response conditioning (Pinker, 2004). In 1949, Donald Hebb hypothesized that synchronous firing of two neurons strengthens the synapse that connects them (Hebb, 1949). This theory, popularized in the phrase "What fires together wires together", has been supported by various studies (Binder & Smith, 2013) and has become a fundamental of modern behaviorism. Based on Hebb's theory, behaviorists suggest that learning as all, regardless of whether verbal or non-verbal happens through the equality fundamental process that is via the formation of habits (Binder & Smith, 2013).

The French neuroscientist Pierre-Paul Broca was busy discovering any sections of the brain that are behind the processes of language, comprehension and speech production as well as control of facial nerves. What we know as "Broca's yard" is located at the back of the lower frontal gyrus where expressive language forms. Broca was the first to associate the place of language with the left hemisphere, and this speech is true and applies to most of us today, but it cannot apply to all brains, it is possible that the center of the language is located on the right side where the convolutions of language are in the brains of about 30% of people who They depend on the left hand, and about 10% of those who use the right hand. At the end of Broca's square is a triangular part that is responsible for understanding the meanings of language (Magrassi et al., 2015). Ten years after Broca's discoveries, the German neuroscientist Carl Wernicke found that Broca's courtyard was not the only one that could lead to language deficiencies. In the Superior Posterior Temporal Lobe, the Vernika Square operates just like its counterpart in the Broca's Court with regard to dealing with the receiving language or the language we hear and treat. The arcuate fasciculus connects the Broca's courtyard with the Virca's courtyard (see Figure 2). If this bundle is damaged, one will find it difficult to repeat what others say (Magrassi et al., 2015).

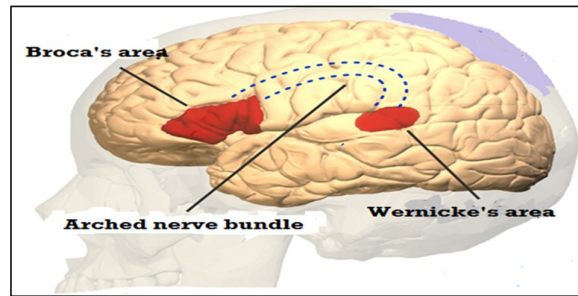


Figure 1. Diagram of language-related regions

A. Second Language Acquisition

Learning and acquiring a second language becomes easier at a young age (before puberty) because the brain will be in this period of time more flexible and learnable and has many reasons and questions about learning the second language to understand and experiment with what he learned and understood in the first language (Kuhl, 2010). Linguistic morphology is the detailed study of words in which understanding of how words are created and how they relate to other words of the same is language. Study in (Havas et al., 2017) talked about the neural signatures in introductory period of morphological guideline based learning of a new languages (second language) in grown-ups and proposes that considerably after a short presentation, grown-up language students can get both novel words and novel morphological principles of second language. Researchers examined structural changes to brain regions accepted to help language jobs during learning of a foreign language. Trial discoveries show that the volume of the hippocampus and the cortical thickness of the left center frontal gyrus, substandard frontal gyrus and unrivaled fleeting gyrus increment for translators contrasted with controls. In interpreters with higher foreign language capacities, the correct hippocampus and the left predominant worldly gyrus were both fundamentally more malleable (Mårtensson et al., 2012; Stein et al., 2012). The study examined the effect of second language acquisition age on the structural and cognitive functions of the learner's brain. This study showed that language skills and current exposure rates to language terms vary according to the age of the learner. Basic changes identified with bilingualism and multilingualism have likewise been accounted for, bilinguals will in general have increased grey matter volume/density in the left caudate and the left second rate parietal structure (Della et al., 2013). Authors in (Antón-Méndez et al., 2015) explored the correlation between instructed second language acquisition (ISLA) skills and identified a clear connection between attitude towards language learning and second language skills. The analysis of language learning achievements in monozygotic and dizygotic twins point to the possibility that having a positive attitude towards language learning and the language class is related to how well students do in ISLA independent of natural language abilities, teacher skill and L1-L2 relations. In (Kepinska et al., 2017) authors analyzed the neural substrates of novel sentence structure learning in a group of healthy adults led a trial and study dependent on fMRI that, as far as useful availability, the inclusion of the brain network during syntax acquisition is combined with one's language learning capacity. Bilingual studies have clearly distinguished methods of neural representation of the second language completely different from the methods of neurological representation of the original or first language. Especially, there are many differences in the activation process between L2 and L1, in size and degree. tend not only the second language are to more neural activity within the original or recognized language regions in the left hemisphere but also to activate many areas outside the traditional language network. The reason for the different signatures or neurological representations of the second language from the neurological representations of the first language is due to the following two hypotheses. The first shows that there is a decrease in the neuroplasticity of the second language learner at a later age, the opposite of the neuroplasticity when learning the first language. Learning the second language wants an increase in the nerve structure of storing and retrieving languages due to the mature changes in neuroplasticity within the areas of first language learning (Li et al., 2014). As for the second (alternative) hypothesis, it is suggested that the neurological differences between learning the original language and learning the second language are due to the fact that second language learners have less language ability than the original language learners, especially when the second language is acquired in later stages, this leads to an increase in neurological resources when Learn any second language (Newman & Tremblay, 2012). The results of previous studies indicated that the age of the language learner and the mental ability of the second language learner describe different functional and structural networks within the bilingual

brain, which we interpret as indicating distinct plasticity forms for age-dependent effects versus experience and/or skills.

B. Acquired Language Disorders

Some may ask whether the language is subject to disturbances after its completion, and the answer is yes, because language is concentrated in specific areas in the human brain, and it is also one of the organs that is subject to partial or total damage at any. Several studies have presented the negative aspects of linguistic brain disorders, the most important of which are Broca's aphasia, Frinka's aphasia and other brain diseases that directly affect the previously acquired language, using several techniques to analyze the extent of the language defect (Dronkers et al., 2007; Baldo et al., 2012; Mechelli et al., 2005). While most studies did not directly address what is the effect of known linguistic brain disorders on learning and acquiring new languages, can the brain assimilate them? Does the linguistically disturbed brain have the acquisition of a new language compared to healthy brains that are not linguistically disturbed under the same criteria and procedures, or is this difficult to achieve.

IV. LITERATURE REVIEW

The most popular recording modality for BCIs is EEG, which measures the summation of electrical activity at the scalp resulting primarily from excitatory and inhibitory post-synaptic potentials in the membranes of cortical neurons (Moghimi et al., 2013; Coyle et al., 2007). Electroencephalography signals are readily recorded without any invasively, by electrodes putted on the Skull. The temporal resolution of this modality is better than that of other non-invasive methods. However, because the signals have to pass from the scalp and skull's bone, dura mater, and other layers of skull and brain, Electroencephalography signals have a poor signal-to-noise ratio (SNR) and because background noise created either inside the mind or outside on the scalp these signals are powerfully influenced. Another shortcoming of Electroencephalography is its poor spatial resolution (~10 mm at best), limiting the ability to localize specific sources of neural activation (Coyle et al., 2007).

TABLE I. LANGUAGE (SPEECH) RECOGNITION SYSTEMS USING EEG OR ECoG

Author & Year	Type of speech	Recording Technique	Data acquisition device	Data Collection	Classifier	Accuracy
(Soman et al., 2019)	Overt	EEG	by an BESS F-32 amplifier consists from 32 passive electrodes	Indian 17 participants from three English , Japanese and Hindi languages	support vector machine (SVM) and linear kernel function	Around 63.32%
(Hashim et al., 2018)	Imagined	EEG	By Emotiv Epoc sensor device consists of 14-channels	Four volunteers have agreed to participate as subjects, all healthy males	k-NN algorithm	About 58%
(Sereshkeh et al., 2017)	Imagined	EEG	BrainAmp consists of sixty-four active electrodes and DC amplifier	By 12 able-bodied fluently English-speaking	Multilayer Perceptron Neural Networks (MLPNN)	About 54.1% $\pm$ 9.7
(Sereshkeh et al., 2017)	Imagined	EEG	BrainAmp consists of sixty-four active electrodes and DC amplifier	Twelve able-bodied individuals (6 male / 6 female)	linear support vector machine (SVM)	Around 69.27%
(Gonzalez-Castaneda et al., 2017)	Imagined	EEG	High resolution channels(14 electrodes) and the fast Fourier transform (FFT)	Data were collected of the EEG signals from 27 individuals whose native language is Spanish	SVM - Naive Bayes is a probabilistic classifier (NB)	83.34%
(Nguyen et al., 2017)	Imagined	EEG	BrainProducts ActiCHamp Includes 64 electrodes with amplifier	From three different types (long words ,short words and vowels)	Relevance Vector Machines classifier (RVM)	the classification of two words about 95% While the three words about 70%
(Herff et al.,2017)	Overt	ECoG	g.USB amplifier (Guger Technologies, Austria) it is consists 16 channel	Data were collected from a 42 year-old female patient.	complex linear model	About 68%

(Ibayashi et al. , 2018)	Overt	ECoG	silicone-coated electrode array (6 micro-needles and 3 macro-electrodes)	Japanese language (15 Japanese syllables)	Sparse Logistic Regression classifier (SLR)	52.0 ± 10.5%
(Martin et al.,2016)	Overt/Imagined	ECoG	via device its name as g.USBamp consist of 16 electrode	From five patients with epilepsy by implanted electrodes in their brain	support vector machine (SVM) And Gaussian kernel	About 88%
(Ramsey et al. , 2017)	Overt	ECoG	128-channels were used micromed recording system (Treviso, Italy)	Get on data were from five intractable epilepsy patients.	Support Vector Machine (SVM) and two filters (SMF filter , SMF filter)	over 75%
(Yoshimura et al., 2016)	Imagined	EEG/fMRI	Thirty-two electrodes were used based on the 10–20 international system	Data was collected of ten healthy human (by two Japanese vowels)	Sparse logistic regression(SLR)	58.5%
(Kang et al., 2015)	Imagined	EEG	Tobii 1750 eye-tracker to detects eye movement of the user , Brainno device (2 channel)	Data were collected of sixty- three participants in English word exam	Support Vector Machine (SVM)	80.16 ± 0.14
(Kumar et al.,2018)	Imagined	EEG	via device its name (Emotiv EPOC+) used as wireless neuroheadset that consists of 14 electrodes	By twenty-three participants recording three categories of object (images, numbers and texts).	using RF classifier to classification three categories of coarse-level	Between 85.20% and 67.03%
(Prat et al. ,2016)	Overt	qEEG	wireless EPOC 16-channel headsets (Emotiv, Australia)	By sixteen participants speaking (French-English)	Mini-Mental State Examination (MMSE)	up to 60% of the variability in SLA,
(Rahma et al.,2019)	Overt	EEG	Four EEG channels were used for recording by a maximum impedance of 15Ω. under 10-20 International System	Data were collected using open brain computer interface and involved sixteen respondents speaking (English).	power spectral density (PSD) analysis	male respondents showed a higher concentration compared with female
(Dave et al., 2017)	Overt	EEG	EEG data was recorded using SCAN (Compumedics Neuroscan) consist from 29 tin-electrodes Included an elastic cap (ElectroCap International)	EEG's data were collected of sixty young adults and thirty-six older adults speaking (English).	power spectral density (PSD) analyses for 1/f neural noise	=
(Grundy et al. ,2017)	Overt	EEG	EEG were used by 64-channel Biosemi ActiveTwo for recording and E-prime 2.0	EEG's data were collected of Forty (20 monolingual and 20 bilingual)	Multi-scale Entropy Analysis (MSE)	monolingual 0.94 and for bilingual 0.93
(Liu et al. ,2017)	Overt	EEG	EEG data was recorded by headset called Muse has seven-channels	EEG data were collected of eleven volunteer speaking (English)	Logistic Regression (Local +Global models) And Multi-task Learning	Between 54.97% and 55.01%

Neurolinguistics is like any other science that has challenges and difficulties, here the most important challenges in the field of neurolinguistics in general, the most important of them are reviewed. Firstly, what is the type of speech produced from the brain is spoken, audible or imaginary only? Secondly what types of the stimuli, and the extent of their linguistic effect on the brain when speaking or learning languages? There another challenge and important is noise produced for the methods used to monitor and analyse languages and their traceability in the brain during speech. What is the result resolution of methods are used to analyse and understand nerve linguistics in the brain? scientists or researchers should to either recognize that they are examining speech perception within huge noise commotion, or utilize online or offline strategies in which speech presentation is timed to avoid noisy periods of data collection or brain stimulation (Devlin & Watkins ,2007).

VI. MOTIVATION

The main defense of this review is the lack of sufficient studies covering the cognitive and functional effects of the brain when acquiring new languages, how to store and retrieve them when needed, and what are the differences between the acquisition of new languages and the mother tongue on brain functions and perception. This review provides a comprehensive knowledge of everything related to neurolinguistics, especially when acquiring a second language.

VII. CONCLUSIONS

In this review, we explained the different methods for handling of EEG signals recorded while learning languages. Some of these methods have advantages as well as constraints. These limitations can be solution it by using one method or merge of two and more In order to obtain accurate and effective results as compared to individual algorithms. Also we have come to the conclusion that studies related to neurolinguistics regarding the effects of learning one or more foreign languages on brain function and perception are still very modest and in their early stages. Also, any partial or total disturbance in the area responsible for language acquisition will lead partial disability or total to acquiring or learning any new languages.

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