



The Effective Brain Areas in Recognition of Dyslexia

Roya Kheyrikhah Shali^{1D}, Seyed Kamaledin Setarehdan^{1D}

School of Electrical and Computer Engineering, College of Engineering, University of Tehran Tehran, Iran

Abstract

Background: The brain has four lobes consist of frontal, parietal, occipital, and temporal. Most researchers have reported that the left occipitotemporal region of the brain, which is the combined region of the occipital and temporal lobes, is less active in children with dyslexia like Sklar, Glaburda, Ashkenazi and Leisman.

Methods: There are different methods and tools to investigate how the brain works, such as magnetic resonance imaging (MRI), positron emission tomography (PET), magneto-encephalography (MEG) and electroencephalography (EEG). Among these, EEG determines the electrical activity of the brain with the electrodes placed on the special areas on the scalp. In this research, we processed the EEG signals of dyslexic children and healthy ones to determine what the areas of the brain are most likely to cause the disease.

Results: For this purpose, we extracted 43 features, including relative spectral power (RSP) features, mean, standard deviation, skewness, kurtosis, Hjorth, and AR parameters. Then an SVM classifier is used to separate two classes. Finally, we show the particular brain activation pattern by calculating the correlation coefficients and co-occurrence matrices, which suggests the activation of the working memory region as an active area.

Conclusion: By identifying the brain areas involved in reading activity, it has expected that psychologists and physicians will be able to design the therapeutic exercises to activate this part of the brain.

Keywords: EEG; Classification; Dyslexia; Occipitotemporal lobe; Signal processing.

*Correspondence to

S. Kamaledin Setarehdan,
School of Electrical and
Computer Engineering, College
of Engineering, University of
Tehran, Tehran, Iran.
Tel: 989121949264
Email: ksetareh@ut.ac.ir

Published online June 21, 2020



Citation: Kheyrikhah Shali R, Setarehdan SK. The Effective Brain Areas in Recognition of Dyslexia. Clin Neurosci J. 2020;7(3):147-152. doi:10.34172/icnj.2020.16.

Introduction

Scientists believe that the human brain is the most complex substrate that has ever existed. The brain can divide into three main parts: cerebrum, cerebellum, and brainstem. The cerebrum is the most critical part of the brain and contains thinking, emotions, movements, and reactions. The outermost layer of the cerebellum is a nerve tissue called the cerebral cortex. The cerebellum consists of two right and left hemispheres. Each of these two hemispheres has four lobes: frontal, parietal, occipital, and temporal.^{1,2}

- Frontal: This section includes personality, emotions, problem-solving, reasoning, planning, parts of the speaking process, and movement.
- Parietal: This section is responsible for feeling (like pain and touch), sensory perception, cognition, stimulus perception, orientation, and movement.
- Occipital: This area of the brain is responsible for visual information processing.
- Temporal: This section includes the recognition of

auditory, speech, perception, and memory stimuli 2.

One of the capabilities of the frontal area is to track a large number of information units simultaneously. This part of the memory is called active memory. Studies have shown that the prefrontal region divided into separate segments for storing different types of information, such as cache memory, storage of the shape of an object or part of the body, the movement, and the others 1, 3. Finally, by combining the sum of these temporary data units from the working memory, we will be able to realize the following capabilities:

- (1) Forecasting, (2) planning for the future, (3) delaying response to incoming sensory signals until the best response and decision are made based on sensory information, (4) considering the consequences of motor actions before performing them, (5) solving Mathematical, legal, or philosophical problems, and (6) controlling all our work to comply with ethical law.
- The combined region of the occipital and temporal part is called the angular gyrus, or the occipitotemporal

cortex. More precisely, this area encompasses the secondary portion of the occipital cortex (vision) and posterior portion of the temporal cortex (hearing).^{1,2} Nowadays, functional imaging studies indicate that the occipitotemporal cortex is less active in dyslexic patients than healthy people—the human reading abilities affected by this area of the brain.^{3,4}

Dyslexia is an inability to read properly despite having sufficient intelligence. Sklar et al claimed that there is a higher association of intrahemispheric and fewer interhemispheric indices in dyslexic subjects during phonological processing.⁵ Galaburda and Kemper showed that dyslexic patients suffer from thalamic dysfunction and asymmetry between the right and left brain regions.⁶ In the following years, with the advent of imaging tools and the ability to observe the activity of the brain, many works have been done to discover active, inactive, and involved points in the reading process. Based on these imaging features, some of the researchers reported that the left occipitotemporal activity in children with dyslexia was lower than in healthy people. Silani et al, for example, used the Voxel Based Morphometry (VBM) to investigate brain gray matter in the left angular gyrus area.⁷

There are different methods to investigate how the brain works such as magnetic resonance imaging (MRI), positron emission tomography (PET), magnetoencephalography (MEG) and electroencephalography (EEG) that all of them are non-invasive approaches. One of these methods is recording and processing the brain signals EEG. EEG is the brain-related electrical potentials recorded from the scalp. These electrodes placed on the scalp in particular positions that specified using the International 10-20 system. Each electrode site labeled with a letter and a number that letter refers to the area of the brain like F for frontal lobe and T for temporal lobe. Even numbers denote the right side of the head and odd numbers on the left side of the head. EEG has different comparative advantages, including high temporal resolution, system simplicity, low cost per test, and the device is portable.²

It should stress that EEG is a sensitive parameter of the subject's state and EEG rhythms change dramatically when the subject falls asleep and transfers from one stage of sleep to another. Sleep spindles disappear while theta and delta rhythms develop at further stages of sleep. During wakefulness, rhythms can be a sensitive measure of brain responses to different psychological tasks. For example, occipital alpha rhythms have suppressed (desynchronized) while frontal beta rhythms are enhanced (synchronized) in response to behaviorally meaningful visual stimuli 1, 2.

The stages of information flow measured by event-related potentials (ERPs). In contrast to EEG rhythms, the necessary condition for eliciting ERPs is time locking to a specific event, either a stimulus or a movement. The tasks that used to elicit ERPs cover a wide variety of human

sensory-motor and cognitive functions.²

Dyslexic research has started in 1972.^{4,8} The main problems observed in the patients were: reading non-fluently, slowly, and with many mistakes. Thereby they have shown a lower rate of learning compares to healthy individuals of the same age. In addition to these, the conditions may differ from one patient to another. Like seeing letters with shift or in reverse.^{3,9,10} As it is clear, all of these problems are essential factors in the learning process at school years. Dyslexic child suffers these consequences despite having a right IQ level and health in hearing and vision.^{11,12}

In this research, we are going to process the EEG signals that have taken from a dyslexic and healthy child during the cognitive tasks. Finally, we identified the brain regions involved in Dyslexia by feature extracting and classification of EEG signals.

Materials and Methods

Data Description

The data used in this study have been obtained in Atiyeh clinic center (www.atiehclinic.com). The sample group consisted of 30 primary school students whose parents wanted to treat their reading difficulties. Patients randomly divided into two experimental and control groups. The experimental group included children who were treated by computer exercises, and the control group received no treatment. The total child's age is 7 to 12 years old. The experimental group consists of 13 boys and 2 girls with a mean Raven intelligence score of 94, and the control group consist of 9 boys and 6 girls with an average Raven intelligence score of 96. Also, 15 healthy children, including eight boys and seven girls with an average Raven Intelligence score of 96, were separately tested. According to the research title, we need only two healthy and patient groups to diagnose the disease, and the third group has only used to evaluate the results. All signals recorded with a Mitsar 19-channel electroencephalograph. The electrodes A1 and A2 were selected as the reference electrode, and the location of the electrodes follows the 10-20 standard.

Signals produced in 5 different states that three of them are cognitive computing tasks. The first and second states are the rest of the brain with open eyes and closed eyes, each of them for 3 minutes. The following is a description of 3 cognitive tasks:

A) 3 minutes presentation of N-Back cognitive task for working memory. In this task, various shapes have shown to the child and asked to press the space bottom if the last shape 9 repeated before otherwise, wait.

B) 3 minutes presentation of visual-spatial N-Back cognitive task. In this task, various shapes have shown to the child that each of them may appear in various places of four corners cadre. This cadre is located in the middle by big pluses to the frame that has roughly divided into

four parts. The child is bound to press the space bottom if s/he has seen the same two consecutive (independent of the location shape). Otherwise, it must wait. Images will appear in the box every 1 second.

C) 7 minutes presentation of Visual P300 (Oddball) cognitive task. In this assignment, spatial shapes will appear at the top or bottom of the box. The child asked if it appears at the top, press the space bottom, and if it is not, does not click.

The EEG signals are in 19 channels and sampled at 250 Hz.

Preprocessing

Initial processing of the data for this study has conducted by standard procedures Pre EEG signals.¹³⁻¹⁵ This process includes the following steps:

- Remove the artifacts using WinEEG software.
- Crossing the Band-pass filter with a frequency bandwidth of 0.5 to 50 Hz.
- Segmenting the signal interval of one second, and putting together similar seconds (same task).

Feature Extraction

Forty-three features extracted for each of the five 19-channel signals that include RSP (relative spectral power) features, mean, standard deviation, skewness, kurtosis, Hjorth parameters, and AR parameters.^{4,16-18}

- **RSP:** RSP is the power ratio in a frequency sub-band to the total power of all sub-bands. Usually, Sub bands are the same delta, theta, Alpha, Sigma, and Beta categorized divisions.^{19,20}
- **Skewness:** This statistical characteristic shows the asymmetry of the distribution form.
- **Kurtosis:** This property measures the rate of smoothness and distribution of the filter relative to the normal distribution.^{21,22}
- **Hjorth parameters:** for a time series, activity, mobility, and complexity of Hjorth, all of which are scalar parameters.²³⁻²⁵
- **AR (auto-regressive):** In this method, the time series is divided into smaller intervals, thus reducing the frequency data decreased. The output at any moment defined as a linear combination of outputs and a white noise input with zero means. This method used for static signals. In the case of non-stationary signals such as an EEG, it should break into intervals of less than 2 seconds in order to assume stationary signal components and use this method.^{26,27} In this research, we used AR with rank 1, 2, 3, and 4 (10 AR coefficients).

Classification

For the classification, a support vector machine (SVM)

classifier used.

- **SVM:** The SVM is a method of monitoring learning that has used for classification and regression. The monitoring means to extract a model based on a set of training data that will have to predict each new instance in terms of categories. The SVM, by creating one or a set of hyperplanes, in a high-dimensional space, but a finite property vector divides it into several separate categories. Finding the super-page that has the most significant distances from the data of all the classes' leads to the best classification.^{28,29}

Results

Forty-three features extracted for each electrode. These features, which have identified as the best features for separation according to the results of scattering test, are:

- 10 RSP characteristics (Relative Spectral Power)
- 15 HP characteristics (harmonic)
- 3 SWI Characteristics (Slow Wave Index)
- 3 Hjorth characteristics
- 2 skewness and kurtosis characteristics
- 10 AR characteristics

In order to classify the SVM used. Classification of 2 to 2 for healthy and the control groups have shown in Tables 1 and 2. Correlation coefficients calculated between 19 electrodes in every five signals. The highest coefficients of each table (greater than 0.95) extracted. These steps performed for each of the five signals from all three groups and the effective electrodes extracted.

To obtain the co-occurring matrix, we consider values less than 0.95 the zero and set values greater than 0.95 the one. Element "1, 1" indicates the number of times that a correlation above 0.95 occurs between the electrodes.

We repeat this process for the second to fifth signals. Effective electrodes obtained in each case, and we can see the results in Tables 3 to 10.

Discussion

As has seen in the tables, effective areas are not the same

Table 1. Part of Table 19x19 Correlation Coefficients Between 19 Electrodes, Healthy-Control Group, the First Signal

	Fp1	Fp2	F3	F4	C3
Fp1	1	0.975	0.747	0.843	0.6
Fp2	0.975	1	0.729	0.827	0.523
F3	0.747	0.729	1	0.76	0.778
F4	0.843	0.827	0.76	1	0.576
C3	0.6	0.523	0.778	0.576	1

Table 2. Co-occurring Electrode Matrix for the First Signal of the Healthy Group

	0	1
0	277	27
1	27	30

Table 3. Part of Table 19x19 Correlation Coefficients Between 19 Electrodes, Healthy-Control Group, the Second Signal

	Fp1	Fp2	F3	F4	C3
Fp1	1	0.7258	0.9595	0.8709	0.9582
Fp2	0.7258	1	0.7776	0.6865	0.5674
F3	0.9595	0.7776	1	0.8332	0.8939
F4	0.8709	0.6865	0.8332	1	0.8077
C3	0.9582	0.5674	0.8939	0.8077	1

Table 4. Co-occurring Electrode Matrix for the Second Signal of the Healthy Group

	0	1
0	295	32
1	32	2

Table 5. Part of Table 19x19 Correlation Coefficients Between 19 Electrodes, Healthy-Control Group, the Third Signal

	Fp1	Fp2	F3	F4	C3
Fp1	1	0.9914	0.9832	0.8588	0.9766
Fp2	0.9914	1	0.9639	0.8409	0.9609
F3	0.9832	0.9639	1	0.9205	0.9814
F4	0.8588	0.8409	0.9205	1	0.8905
C3	0.9766	0.9609	0.9814	0.8905	1

for all children. In the case of the first two signals, with the individual differences in the effective electrodes, Fp1 and Fp2 are common to all. The Fp1 and Fp2 belong to the prefrontal region. The brain of a healthy human creates an alpha wave in the resting state. This wave usually comes out from the occipital, frontal and parietal lobe 1. On the other hand, according to the age of the subjects, it is expected to appear the alpha range.^{1,2} Thus, these electrodes are compatible with the brain-behavior. In the case of the last three signals in addition to the individual differences between the effective areas, all electrodes are not common among children, and only a few of them are the same to all. For example, in the third signal, the effective electrodes are Fp1, Fp2, F3, C3, O2, and O1. While each of the children has a number of these six electrodes and does not have all numbers. The only common electrode for all children, in this case, is the F3 electrode. Alternatively, in the fourth signal, the effective electrodes obtained are Fp1, F3, Fz, C3, and Cz, whereas only Fp1 and F3 electrodes are the same among all nine. The same conditions apply to the fifth signal. On the other side, the repeat of electrodes Fp1, Fp2, F3, and C3 is higher than all electrodes in all of the signals and children.

The third signal encompasses the frontal, parietal, and prefrontal regions. Similarly, for the fourth and fifth signals, the left (F3 and F7), Cz and C7 central electrodes, and the left parietal electrode “P3” are the most effective electrodes. Arns et al showed that there is more relation

between the Frontal, Central, and Temporal electrodes than the other areas during the reading and phonological processing.⁹ Klimesch and colleagues demonstrated in their study that Occipital, Parietal and Temporal lobes have the most significant differences between the healthy child and dyslexic ones.⁴ This information shows that the effective areas in the third, fourth, and fifth signals are also compatible with the brain activities and working memory region.

In the case of differences between individuals, in some children, the visual forces are more involved, in others the thinking forces and so on. The reason for these differences is the difference between people using forces to do the same thing. Psychologists believe that some people are more careful in reading letters, some using sounds, and the others using their meanings. Also, the gender of children affects the functioning of different brain regions. These individual differences cause different areas of the brain to be involved in people while doing the same thing. By identifying the brain areas involved in the reading activity and cognitive tasks, it has expected that psychologists and physicians will be able to design the therapeutic exercises. Also, expand data to children aged less can be more effective because we tend to identify dyslexic children at an early age, preferably before school and in a straightforward way. Thus, there is enough time to cure and do treatments before starting school. So the reduction in the age range of the subjects can be useful in achieving more accurate results. The ERP issue is a powerful and interpretable tool to extract the differences between healthy and dyslexic children. It has hoped that it

Table 6. Co-occurring Electrode Matrix for the Third Signal of the Healthy Group

	0	1
0	301	29
1	29	2

Table 7. Part of Table 19x19 Correlation Coefficients Between 19 Electrodes, Healthy-Control Group, the Fourth Signal

	Fp1	Fp2	F3	F4	C3
Fp1	1	0.9866	0.8576	0.7968	0.6113
Fp2	0.9866	1	0.8155	0.8194	0.5697
F3	0.8576	0.8155	1	0.8251	0.8377
F4	0.7968	0.8194	0.8251	1	0.7118
C3	0.6113	0.5697	0.8377	0.7118	1

Table 8. Co-occurring Electrode Matrix for the Fourth Signal of the Healthy Group

	0	1
0	268	34
1	34	25

Table 9. Part of Table 19x19 Correlation Coefficients Between 19 Electrodes, Healthy-Control Group, the Fifth Signal

	Fp1	Fp2	F3	F4	C3
Fp1	1	0.7204	0.9913	0.8036	0.9399
Fp2	0.7204	1	0.7609	0.8805	0.5294
F3	0.9913	0.7609	1	0.8166	0.9226
F4	0.8036	0.8805	0.8166	1	0.6200
C3	0.9399	0.5294	0.9226	0.6200	1

Table 10. Co-occurring Electrode Matrix for the Fifth Signal of the Healthy Group

	0	1
0	249	41
1	41	30

will be followed up processing and future research in the case of dyslexia.

Conflict of Interest

The authors declare that they have no conflict of interests.

Ethical Statement

The data used in this study have been obtained in Atiyeh clinic center (<http://atiyehclinic.com>). All data are obtained from children in standard conditions and with their parental permission. I state that all the people and institutions involved in this project mentioned, and all the research progress has been conducted with the supervision and awareness of them and under ethics.

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