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Detection of Autism with Electroencephalographic Signals and Comparison with Healthy People Using Genetic Algorithm Network

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Abstract

Autism, also called autism spectrum disorder (ASD), is a complicated condition that includes problems with communication and behavior. It can involve a wide range of symptoms and skills. ASD can be a minor problem or a disability that needs full-time care in a special facility. People with autism have trouble with communication. They have trouble understanding what other people think and feel. This makes it hard for them to express themselves, either with words or through gestures, facial expressions, and touch. According to the Centers for Disease Control, autism affects an estimated 1 in 59 children today. Indicators of autism usually appear by age 2 or 3. Some associated development delays can appear even earlier, and often, it can be diagnosed as early as 18 months. Research shows that early intervention leads to positive outcomes later in life for people with autism. In this paper, we describe an Autism detection algorithm that runs over electroencephalography (EEG) signals. Because this technique comprises different parameters that significantly affect the detection performance, we will use genetic algorithms (GAs) to optimize these parameters to improve the detection accuracy. And in the end, the results have been compared statistically by the T-test. In this paper, we describe the GA setup. EEG signals of 20 children with Autism and 20 healthy children aged 6 to 12 years have been obtained. The results have been compared. Lower correlation levels between resources of the left hemisphere of the brain especially C3 channels region in autistic children compared with healthy subjects have been observed. Also, the average energy of theta frequency band in C3 and F3 channels for children with autism was lower than that in healthy people and this criterion was higher in the gamma frequency band.

Keywords: Electroencephalography, Autism disorder, Genetic Algorithms, Fitness Function, T-test.

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1. INTRODUCTION

Autism was first introduced by Leo Canner [1]. Therefore, it is sometimes referred to as canner syndrome. Autism, a neurological disorder with psychological symptoms is usually in the first 3 years of life. So, the abnormalities in social interaction are seen and imagination individual associated [2]. statistics SunYuas the disease each year one, two, four and six out of every 6 people mentioned. [3-6]. Various analyses of Electroencephalography (EEG) signals have been performed to help diagnose the disease. In 2007, Sheikhani et al. investigated the EEG of autistic people using Lempel-Ziv (Lz) and Fourier Time Quadratic Conversion (Short Time Fourier Transform, STFT) methods, which, after evaluating the results and classification, between the two healthy groups and autism produced an 81% differentiation [7]. In 2007, Elena studied the high frequencies power spectrum of two autistic groups in the age range of 2–5 years in two different cities of Moscow and Gothenburg, and in both cases, it was demonstrated that a pathogenic increase in gamma band activity occurred depending on the spatial distance of the electrodes from the sources of muscle artifact production [8]. In another study using EEG signal spectrogram analysis, the largest difference was observed between the two groups of autistic and healthy subjects in the open-eye recording conditions and the alpha band [9]. In addition to impaired social behavior, visual perception is also recognized as part of the apparent structure of the autism spectrum and this abnormality has been reported with poor central correlations and a decrease in the integrity of brain signals in people with autism disorder [10]. According to the results of a study by Van Stein Varrentin [25], Griessen, and Sheikhani [7], the mean gamma band frequency in some components of the left hemisphere is lower for autistic children than for healthy children in the upper theta band. Alena's results showed that in children with autism, the correlation of the left hemisphere components with that of other children was lower than in healthy children since the left hemisphere was associated with a lack of interaction in this area in autistic children [8]. In an article on EEG signal processing, Behbahani and Ali Modi used a server-based wavelet entropy method to investigate the relationship between the degree of hypnosis. Hossein Saffari-nia, Mohammad Reza Ahmadzadeh, Jafarmohori, in 2007 used approximate entropy and standard deviation of EEG signal to diagnose epilepsy. The approximate entropy value and the standard deviation of the signal during an epileptic seizure decrease and increase in the order that this feature is used in their proposed system. In another study, the year 2008, they evaluated the signals of autistic children and healthy children using STFT and Coherence Function. Using coincidence similarity, it has been observed that in autistic children there are differences in the channels within the frontal and parietal lobe areas as well as the relationship between this lobe and the central lobe. In another study, between two groups of healthy and autistic individuals using EEG signal spectrogram analysis, the most significant difference was in open-eye conditions and the alpha band [24]. Studies have shown a difference between the EEG signal of autistic people and healthy controls.

EEG signals are a combination of the potential of a myriad of neurons. One of the most applicable methods for the diagnosis of autism is the use of an electroencephalographic signal because these signals accurately represent brain function. In this paper, we present the use of electroencephalographic signals for the diagnosis of healthy children with autism. For this purpose, after recording the signal from 40 autistic and healthy children aged 6 to 12 years using the openBCI device, the necessary features will be extracted. Then based on the proposed model the diagnosis is performed. Because several parameters are critical to performance detection, these are optimized using genetic algorithms. Statistical analysis was then performed using a t-test with a significance level of 5%.

This paper is structured as follows: first, it provides the biomedical background required to properly understand this paper's contribution, including the structure of EEG data and how it can be used to perform energy-based autism detection. Then we explain the process for genetic algorithms, delving into its encoding and fitness function. Since a preliminary evaluation is carried out to validate our proposal, its setup, methodology and results are described in the end. Finally, we present conclusive remarks to summarize the paper and highlight its main accomplishments, while at the same time we propose some future work to keep exploring this research line.

2. BACKGROUND

First of all, it is worth noting that EEG is the name given to both the collection of the waves measured in the brain and the technique used for measuring those waves. We are going to use both terms indistinctly along with this paper. With respect to the acquisition technique, the EEG data used in this paper follows the international 10-20 system, which defines the location of scalp electrodes [11]. Brain wave measurements come from the change in potential from neurons. However, it is impossible to record the activity of a single neuron with a surface EEG and therefore its final measurement will correspond to the depolarization and repolarization of thousands or millions of neurons. Notice that neurons must fire synchronously. Hence, the final measurement of the EEG will be the level of excitability of different parts of the brain and the intensity and form of the brain wave will be determined by the number of neurons acting together. Between the EEG signals, it is possible to distinguish different rhythmic activities depending on their frequency. EEG rhythms have been established as follows: Delta Waves (0.5– 4 Hz) appear during deep sleep and sometimes during some severe organic brain diseases, Theta Waves (4–8 Hz) are related with some activity in children but also with emotional stress in adults and they may appear in some neurological diseases as degenerative ones, Alpha Waves (8–13 Hz), which are found in normal adults when they are awake but relaxed and Beta Waves (13–30 Hz), related with any type of mental activity. Gamma Waves (over 30 Hz) have been traditionally included in the range of Beta Waves but up to now, there is no agreement about their function. These frequency bands are not arbitrary but rather arose from some specific distribution over the scalp. Figure 1 shows the different rhythms.

The topographic map in Figure 2 plots a representative sequence of the acquired results for the two children with ASD. the energy during autistic boy brain activity (see Figure 2a) and during an autistic girl (see Figure 2b) over the scalp surface. The analysis of their brain activity was based on their alpha and beta rhythms, through power spectrum density. Through the software Matlab 1.8 (R2013a), the analysis of the power spectrum density was characterized by obtaining the first 1024 samples from the brain signals. The analysis of the power spectrum density shows the most active brain areas (highlighted in more intense color). Both brain activities (Fig. 2a and b) indicate alpha rhythms more pronounced in the occipital regions and beta rhythms more pronounced in the frontal regions.

3. EEG SIGNAL RECORDING

3.1. Data Collection

In this study, 20 children with autistic disorder (16 males and 4 females; mean age 6 to 12) were involved. These children were at a school for autistic disease in Qazvin. These children by two Psychiatrists of children and the use of standard diagnostic America "(DSM-IV-TR) measured and presented [12]. Healthy children included 20 patients (12 boys and 8 girls; mean age 6 to 12) those with no history of mental illness and pre-activity (ADHD) were selected. The signal recording conditions used in this study are open-eye protocols because recent work has yielded good results using this protocol [13]. All children participated in this study were with full consent. Subjects were seated on a chair in a quiet, comfortable room during the experiment and were asked to make the slightest movement to minimize the artifact in the recorded signals. The signal duration was 5 to 10 minutes per person.

3.2. OpenBCI

OpenBCI is an open-source brain-computer interface platform [27] created by Joel Murphy and Conor Russomanno, after a successful Kickstarter campaign in late 2013. OpenBCI boards can be used to measure and

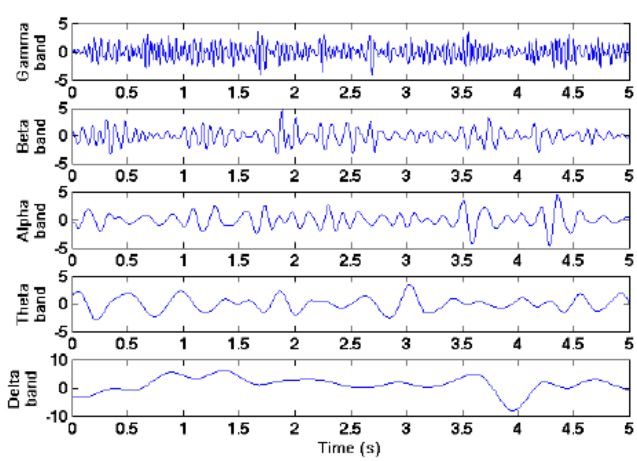


Fig. 1. Different rhythms of EEG signals.

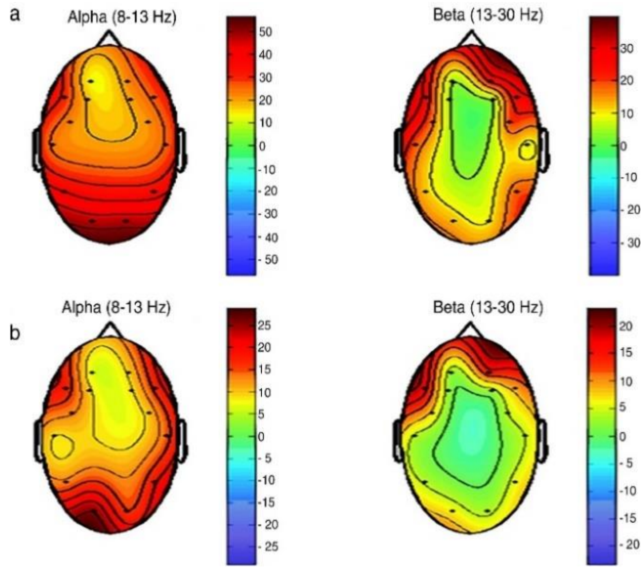


Fig. 2. Brain activations characterized by the alpha and beta rhythms of the boy (a) and girl (b) with ASD.

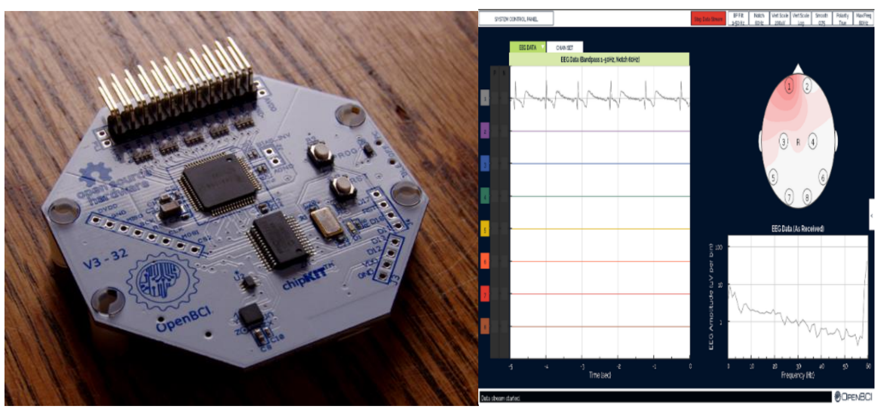


Fig. 3. OpenBCI device and its application [28].

record electrical activity produced by the brain (EEG), muscles (EMG), and heart (EKG), and is compatible with standard EEG electrodes. The OpenBCI boards can be used with the open-source OpenBCI GUI, or they can be integrated with other open-source EEG signal processing tools. OpenBCI has released an open-source application for use with the OpenBCI, written with Processing. Display and processing software written in NodeJS and Python are also available [28].

Figure 3 shows the OpenBCI device and its application.

3.3. EEG Electroencephalographic Signals

Electro-encephalography is one of the essential tools in the evaluation and identification of neurophysiological disorders. Brain signal recording is a noninvasive, painless, and inexpensive method [29]. The electrodes are usually positioned symmetrically on the scalp to record brain signals. These electrodes measure the very low voltages that scientists believe are caused by the simultaneous activity of different neurons of the outer cortex. The intensity of brain waves on the skull surface varies between zero and 200 mV, and their frequency range is from 4 to 50 Hz or more [14], [15].

4. FEATURE EXTRACTION

4.1. Participants

As said before, the children are seated on a chair in a quiet room and a signal is recorded. Signaling is more time-consuming in autistic children because they are less co-operative and therefore a longer time is needed to extract the appropriate signal. In order to record the EEG signal, we put electrodes on the scalp of a child in standard 10-20 system-specific models. According to the standard 10-20, the electrodes were mounted on a special gel, the sampling rate was 256Hz and the output of 21 channels called FP1, FP2, F8, F4, Fz, F3, F7, T4, C4, CZ, C3, T3, T6, P4, Pz, P3, T5, O2, O1, A1, A2 were used. However, two electrodes A1 and A2 were considered as a potential reference. The signal was recorded for each person for more than 20 minutes. The channel information was provided as an array and its channel information was read into the MATLAB software environment. EEG signals were stored in artifact-free intervals for 7 seconds.

4.2. Registration of EEG

For this experiment, a brain-computer interface was used to receive brain signals from people. This brain-computer interface is called OpenBCI. With the help of this device, people receive brain signals and they enter the computer via Bluetooth. We can place electrodes on different parts of the brain. In this study, 21 electrodes of silver and a cap were used to capture electrical waves of the movement of brain neurons. It also has a 10-20 cream that has adhesion and keeps the electrodes in place until the end of the test. This gel has been used to better pass electric current and reduce scalp resistance. After the signals were entered into the computer via Bluetooth, we saw it in real-time in the Java Processing software. This software is open source and implements an EEG lab's analysis in real-time. The base of Arduino programming in C ++ language. EEGLAB is a toolbox and graphical interface in MATLAB, which is used to process EEG signals. The data from the brain will be entered into the Toolbox and the analysis of the signals will be done. With this toolbox, we will have the ability to filter, remove artifacts, put FFT, wavelet, put our experiment events, observe the behavior of the signals of each channel individually, and so on [30].

We applied a low-pass filter and a high-pass filter to the signal. By doing this, only a subset of the signal frequencies is considered. Depending on the values of flo and fhi, this could leave one or several frequency bands such as delta, theta, alpha, etc.

Then we compute the energy of a signal using equation (1),t.

$$\mathrm{E(t)} = \left(\frac{1}{L}\right)^{1} \sum_{i=t-L/2}^{i=t+L/2} x^{2}(\mathrm{i}) \qquad (1)$$

Wavelet transforms as a general mathematical tool for signal processing has many applications in analyzing EEG data.

Wavelet conversion has no Fourier constraint and is, therefore, suitable for recording moving signals [31]. A set of wavelet functions is usually derived from the mother wavelet (ht) which is normalized to a = 2m and b = k2m.

$$\mathrm{H}_{\mathrm{m},\mathrm{k}}(\mathrm{t}) = \frac{1}{\sqrt{\mathrm{a}}}\mathrm{h}\left(\frac{\mathrm{t}-\mathrm{b}}{\mathrm{a}}\right) = \frac{1}{\sqrt{2^\wedge m}}\, h(2^{-m}\, t - k) \quad (2)$$

Integers K and M are defined by solving a dilation equation (2) or analytic expression. Both discrete and continuous signals can be approximated by the Fourier series and Fourier transforms in this way. A set of special band wavelets can be filtered for signal analysis and Apply to classify them.

4.3. Genetic Algorithm

In the previous section, we have described the different stages for signal detection, which comprise different parameters whose values are not known in advance. In this section, we will explain how the different parameters affect the detection performance and describe a genetic algorithm for optimizing their values.

The ANFIS is one of the most common fuzzy nervous systems that runs a Sugeno fuzzy system on a neural structure. This technology takes advantage of fuzzy neural networks such as parallelism and learning in data-rich environments. In these systems, neural networks are used as determinants of fuzzy system parameters. The ANFIS architecture can be considered based on the THEN - IF fuzzy rules, which have five layers [32]. Figure 4 shows the structure of the equivalent of the ANFIS.

In Figure 4, x, y are the node entries to the i node, and Bi-2 or Ai are the names of the linguistic variables corresponding to these nodes. Layers specify the number of layers. In the first layer, entries pass the membership function. The output of the second layer is the multiplication of the input signals. 'w' denotes the weight of each layer, the third layer is normalized to the previous layer. F represents the total output of the system.

5. SUGGESTED MODEL

In this study, using the OpenBCI device, the EEG signal was obtained from 20 healthy individuals and 20 persons with autism. By using Wavelet feature extraction techniques, the signal properties were extracted and trained as input to the fuzzy neural network. Figure 5 shows the framework of the proposed model.

After implementing the autism detection algorithm and optimizing its parameters, we have carried out experiments to evaluate the detection accuracy. In this section we describe the data set used, the experimental setup and the results obtained, discussing and comparing them with other works in the literature [21]- [23]. In this paper, we have used EEG recordings from 20 children with autistic disorder (16 boys and 4 girls; mean age 6 to 12). These children were at a school because of the autistic Qazvin. Healthy children included 20 persons (12 boys and 8 girls; mean age 6 to 12). We recruited subjects from the Syntech Research Institute located in Qazvin, Iran. EEG brain signals using 21 electrodes with a sampling rate of 256Hz at 21 channels FP1, FP2, F8, F4, Fz, F3, F7, T4, C4, CZ, C3, T3, T6, P4, Pz, P3, T5, O2, O1, A1, A2 were used. However, two electrodes A1 and A2 were considered as a potential reference. The signal was recorded for each person for more than 20 minutes.

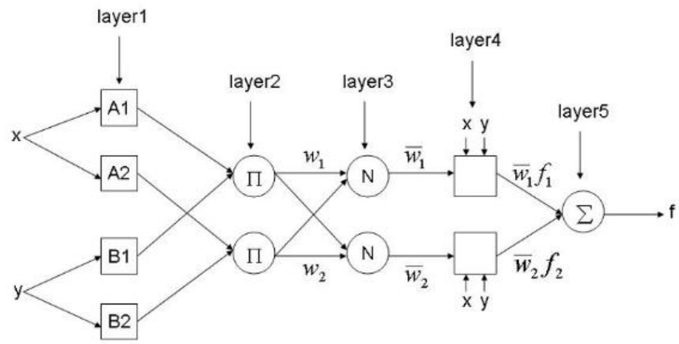


Fig. 4. The structure of the equivalent of the ANFIS [37].

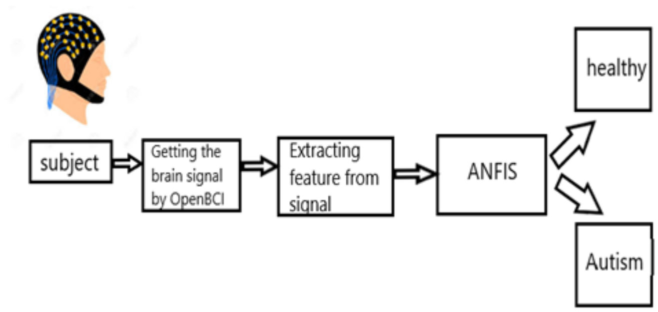


Fig. 5. Suggested model.

The channel information was provided as an array and its channel information was read into the MATLAB software environment. EEG signals were stored in artifact-free intervals for 7 seconds.

Most of them contain 21 EEG signals, yet some might have a few more. The recording was performed with a sampling frequency of 256 Hz and with 16-bit resolution. The recordings belonging to these cases will be used for fitness computation. The autism detection performance will be evaluated over the remaining 40 cases. Testing the performance over a test set different from the training set is a common approach for solving machine learning problems, in order to avoid biased results from overfitting the training data. Figure 6 shows autistic children while they cooperate for signal acquisition.

In this study,850 data were used for training of each feature, and the same for testing. In each step, the error was obtained from training and testing. The results of the autism detection for each patient are shown in Table 1. In order to compute the false positive and false negative rates per hour, the table also displays the total patient's recording duration of the EEG signal. It can be seen how the detection algorithm performance largely depends on the patient. For instance, for the first 20 patients, it takes a long time because they are autisms and for the next 20 persons, it takes a short time because they are healthy.

In some patients the detection accuracy is perfect, having few or none false positives, such as for patients 2, 3 and 4. In contrast,

Fig. 6. Signaling of a number of autistic children.

some patients are yielding very low performance: it is remarkable for patients 6, 7, and 11 where no autism is detected at all, despite the patients are suffering from a higher autistic disorder in all cases. Besides, the method is detecting very few false positives, with an average of 0.43 per 24 hours, which is better than most of the works in the state of the art.

The genetic algorithm was run with the next setup: the population size was P = 40. The stop condition was set when the GA best individual did not change over 50 generations. To speed up the fitness computation, Apache Spark [16] was used. The process was parallelized to run in one physical server with 8 CPU cores, with the recording being the unit of parallelism. C.

These values between the two groups of autistic and healthy using t-test analysis ($p<0.05$) were compared with the results of this calculation written in Table 1. As seen, between some resources with other sources in the brain in healthy subjects and autism significant difference in a way that people with autism this resource has a low correlation with each other compared to healthy subjects. In order to check the location of the observed differences at the brain level, the correlation coefficients of the sources identified in Table 1 with the EEG signal recording channels were calculated.

Shown s5, s8, s12, s17 indicates a significant difference between the two groups in that source.

As was investigated, the highest correlation value is for channel 9, and channel C3.

In another study, correlations of resources that had a significant difference between the two groups were calculated with lobes of different brain regions, with the highest correlation being in the majority of the left hemisphere (C3, F3, and P3).

Table 1. ***Results of autism detection.***

cases	True Positive	False Negative	False Positive	Hours (min)
C1	6	4	7	33
C2	1	7	0	35
C3	5	3	0	36
C4	4	6	0	40
C5	2	7	2	45
C6	0	1	3	46
C7	0	1	4	53
C8	5	14	3	50
C9	4	4	2	34
C10	3	3	6	36
C11	0	2	1	45
C12	2	17	0	66
C13	1	5	1	61
C14	5	8	0	66
C15	4	3	3	45
C16	6	2	5	56
C17	2	18	0	67
C18	3	4	0	58
C19	7	2	0	54
C20	2	2	0	49
C21	2	2	3	12
C22	5	1	2	10
C23	4	6	5	11
C24	4	5	4	19
C25	4	10	3	20
C26	1	4	3	20
C27	2	5	1	25
C28	1	19	1	19
C29	2	33	3	30
C30	5	5	0	27
C31	4	8	0	35
C32	3	4	3	20
C33	3	4	4	29
C34	4	11	6	33
C35	3	0	1	37
C36	1	1	1	40
C37	4	5	4	28
C38	3	4	3	30
C39	2	3	2	29
C40	5	2	3	23

Some sources of the two groups make a significant difference in gangs belong to the theta and gamma frequencies. The mean bandwidth of the theta frequency band in the left hemisphere resources, especially the C3 and F3 channels, was lower for autistic subjects than for healthy subjects, and this value was higher in the gamma frequency band.

On the other hand, the signal sources energy of the two groups were compared in time domain. As shown in Figure 5, in healthy individuals, more energy is concentrated on fewer sources, which means that energy distribution can be expressed with fewer sources, indicating a greater dependence on these sources. In fact, the energy sources of the autism signal are almost identical. It is distributed to all sources and their energy cannot be expressed Since the diagnosis of autism is a challenge in medical science, we sought a strategy to accurately diagnose these patients from healthy subjects.

6. CONCLUSION AND FUTURE WORK

For this purpose, a model based on ANFIS was developed for separating children with autism and healthy children. After recording the signal from healthy and autistic individuals using OpenBCI, which is a precise instrument for electroencephalo-graphic signal recording, we extracted the characteristics of the recorded signals. Among the available features, the wavelet feature was extracted due to the higher performance of the signals. These attributes were considered as the inputs of the interface. In this study, the independent components of EEG signals for 20 healthy and 20 autism children Have been analyzed in the time and frequency domains. And the results of the two groups with T-test and for $p<0.05$ were compared with each other. The results showed that in children with autism, correlation in the left hemisphere (including channels C3, F3, and P3) is lower than in other areas in comparison with the healthy children.

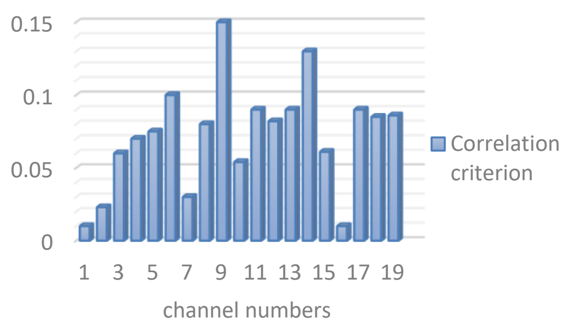
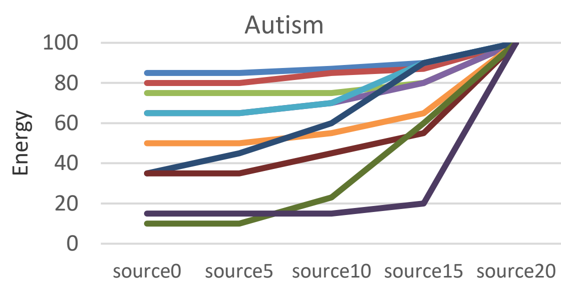
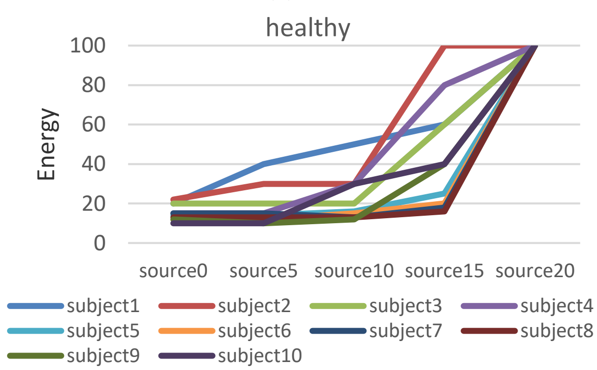


Fig. 7. Correlation between source S1 (one of the sources in Table 1) and channels recorded in an autistic child.



(a)



(b)

Fig. 8. Energy distribution of EEG signals between different sources (a): Autism and (b): healthy.

Table 2. ***Differences between resources each person, in two groups using the t-test (p<0.05).***

P-value	Healthy group (Average+ Standard deviation)	Patient group (Average+ Standard deviation)	source
0.65	4.234∓1.456	3.45∓2.19	ch1
0.34	3.560∓2.654	3.98∓1.94	ch2
0.29	2.980∓1.342	5.29∓3.41	ch3
0.37	3.701∓2.341	6.23∓1.82	ch4
0.01	5.01∓1.349	4.23∓2.33	ch5
0.19	4.560∓2.80	5.34∓3.32	ch6
0.96	3.678∓3.90	6.12∓1.07	ch7
0.03	6.82∓1.763	5.39∓2.08	ch8
0.54	6.03∓1.80	6.76∓1.87	ch9
0.32	5.78∓1.25	5.23∓1.56	ch10
0.34	4.700∓2.32	5.89∓1.90	ch11
0.04	4.498∓1.87	4.65∓3.21	ch12
0.17	5.20∓2.64	4.90∓1.45	ch13
0.87	4.198∓2.78	5.54∓2.20	ch14
0.25	5.54∓1.25	5.76∓1.54	ch15
0.17	5.789∓2.09	5.09∓2.40	ch16
0.04	6.23∓1.09	6.87∓1.23	ch17
0.37	4.34∓1.20	4.4∓1.29	ch18
0.23	5.76∓1.34	4.98∓2.30	ch19

Since the left hemisphere shows the speech activity, lack of engagement in the area of children with autism can be one reason for talking problems as the most important characteristics of this disease [17]. The area is consistent with the results of the Behnam study [18]. Also, the average gamma frequency band in some components of the left hemisphere is higher for autistic children than for healthy ones and for the theta band lower. The difference in the gamma band with reviews von Stein and Sarnthein [19], Grice [20] and Sheikhani [9] is consistent. Therefore, the correlation analysis is useful for the existence of differences in the area of the left hemisphere of the brain in people with autism or healthy.

among other results specifically in this study achieved the sources of EEG signals in healthy people as a group and set in different parts of the brain interact, but in people with autism, the integration of resources in production signal loss and the effects on the level of resources almost uniformly distributed.

As a result of this reporting of the detection and isolation of people with autism and healthy can be useful, however, for the purpose of operational data is needed.

After evolving the autism detection parameters, the algorithm is evaluated over the EEG Data from 40 persons. Results show that the algorithm performance is very diverse. On the other hand, the number of false positives is very small, around 0.43 per 24 hours on average, less than most state-of-the-art works. These results suggest that this method may not be adequate for certain patients. Still, some potential solutions are described in the paper, which left for future work. These include a more diverse set of patients in the training set, learning different parameters for different groups of patients (after a preliminary clustering stage) or giving a higher weight to false negatives over false positives in the fitness function. Additional future work to extend this research would be to use evolutionary strategies to evolve the algorithm parameters, encoding them directly as a vector of real values. More interestingly, multi-objective evolutionary algorithms could be used to optimize different objectives. These objectives could be, in order of importance: increasing the accuracy (thus reducing false negatives), reducing false positives and reducing onset errors. Exploring the Pareto front could enable us to decide on a tradeoff between the first two objectives. In either case, the fitness function used for computing these metrics could be affected by the suggestions proposed before to improve the performance of energy-based autism detection.

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