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Research Article

Processing ECoG Brain Signals to Predict the Movement of the Fingers using the Adaptive Neuro-Fuzzy Inference Systems

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Abstract

Introduction and Objectives: *The human brain has always been regarded as a complex system, and various scholars pay attention it from different aspects. Neuroscientists are seeking to discover the mechanisms of the nerves and find a model that can be used to explain the structure and function, such as perception and emotions related to the nervous system. Therefore, the present study was conducted with the aim of processing ECoG brain signals in order to predict fingers movement using adaptive neuro-fuzzy inference systems.*
Materials and methods: *The data used in this study consisted of the fourth data collection of the series BCI2008 tournament. In the case of using neuro-fuzzy inference system average classification accuracy of moving first, second, third, fourth and fifth fingers 89.8% obtained. In this process, because it requires signal percent to higher noise, the ECoG brain signals have been used. So, classification of brain signals at a frequency of 100-200 Hz and the characteristics of DCT, and using classification of networks of adaptive neuro fuzzy inference system were obtained.*
Results: *in the implementation, the best results was for classification of brain signals at a frequency of 100-200 Hz and the characteristics of DCT, and using classification of networks of adaptive neuro-fuzzy inference system were obtained.*
Conclusion*: as a result of improving the classification, a combination of genetic and fuzzy algorithms and PSO to improve the fuzzy model parameters used.*

Keywords: *Brain computer interface (BCI), brain signals ECoG, Adaptive Neuro Fuzzy Inference System (ANFIS)*

1. Introduction

The human brain has always been regarded as a complex system, and various scholars pay attention it from different aspects. Neuroscientists are seeking to discover the mechanisms of the nerves and find a model that can be used to explain the structure and function, such as perception and emotions related to the nervous system. Artificial intelligence and robotics experts also seek artificial means and computational model that can be emulated brain and so-called thinks (Pakravan. 2010).

Today, this wide spectrum leading to the creation of new disciplines and the brain can be examined from different aspects. Brain cognitive neuroscience and computational and neural systems in recent years with the interdisciplinary approach to the study of the brain are more comprehensive. The discovery of brain signals and technological progress, the possibility of creating interfaces between the brain and the world around it has been scientifically presented that Brain-Computer-Interface abbreviated BCI. Brain-computer interface system is a system that connects the brain with the outside world without using the internal nerves. This system is based on magnetic and electric fields caused by the neuron activity of nerve cells. All interactions in the small neural cells occur during a certain mental activity is visible in the form of an electrical signal. Concept at the first International Conference on BCI Research in 1999 is provided for BCI, includes: "a brain-computer interface is a communication system is not related to normal output of peripheral and muscle nervous system" (T. M. Blakely. 2014).

Hans Berger in 1929 picks up brain signals first time. After the research was conducted in order to identify brain signals fluctuations that lead to alpha waves were detected. Scientists from the early 1970s began its activities in the field of BCI. At the time, Jacques Vidal, professor retired from University of California conducted the project "brain computer interface" with the support of the University. During this time, researchers with simple sensors installed BCI in mice, monkeys, and humans, experiments carried out in this field. Grey Walter in 1964 announced the first prototype of BCI devices based on the assumption that turn on and off a switch operated by a person. In the late 1990s, researchers at Georgia Institute of

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Technology, in cooperation with the University of Emory, by installing a skin membrane electrode in the brain of patients with paralyzed below the neck area had lost his power of speech, the therapeutic potential of BCI displayed. The technique used in the surgery, the patient was able to communicate with the computer, move the cursor. In 1999, clinical faculties MCP Hahnemann, in collaboration with researchers Medical University of Duke, mice was trained to use their brain signals to move an electric water valve (Samii, 2009).

The BCI, communication is focused only on brain signals. The purpose of this communication is primarily helping people with disabilities in relation to their surrounding environment and cannot interact with the surroundings by conventional channels. These people have healthy brains or relatively healthy but are not able to communicate well with their surroundings.

BCI applications, especially in cases the ability to move and communicate with the environment is impaired, but human perception and cognition of man left without blemish. There are many neurological diseases can cause such defects, including spinal injuries. Other diseases include cerebral palsy, spinal muscular atrophies, muscular dystrophy, and limb loss named. Therefore, BCI helps in these cases a computer used as prosthesis. Accordingly, the person is amputation may use a mechanical aid. The BCI can use instead of the computer's mouse. The construction of systems BCI, there are two main approaches. One approach is the use of synchronous systems. If we want to have a general definition of synchronous BCI systems are systems commands and individual performance as well as operating time intervals, already been identified by the system. The second approach, making the BCI systems is asynchronous (Nosrat Arash, 2012). Synchronous systems created limitations for the user that to a large extent in the system is removed. The functionality and performance periods by the person was done.

However, in practice, making these systems than synchronous systems is very difficult. According to needs that are practical for patients and disabled users, synchronous systems are not supplied these needs and bias studies, and research on brain computer interface is to implement asynchronous systems. The main subject of this study is based on solving one of the BCI issues where, in particular, for relations between the fingers movement and brain signals. The used data is related to the tournament BCI2008 and three patients with epilepsy and for synchronization is recorded in this study, first person data was processed. In the signal registration step, the patient is given indications that the determined finger movement and moves the finger at the same time; the patient's brain signals are recorded. The present study was conducted with the aim of processing ECoG brain signals in order to predict fingers movement using adaptive neuro-fuzzy inference systems.

2. The introduction of data

Part of the research in the field of BCI systems provides new methods in the field, holding BCI competitions. The first period of the tournament was held in 2000, and in the years 2003, 2005 and 2008 has continued. The fourth set of the tournament BCI2008 related to figures movement estimation through the process brain signals, which is set as the primary data used in this study. Details on the introduction of research data from references (Pakravan. 2010), (Samii, 2009) and (Ogel J, 2015) written. The data in (Nosrat Arash, 2012) are available.

2.1 Recording data

Examples of this set are related to three epileptic patients with their consent, and as ECoG, the electrodes placed on the surface of the brain are recorded. Digital signal reinforced; that it by Synamps2 amplifiers with 64 monopolar channels as well as internal noise reduction systems are done and then save the files in the mat format and given them to the people.

On the surface of the brain, each patient is assigned to an array of platinum electrodes. Each array contains 48 to 64 members are as 8x8 or 8x6 (respectively 62, 48, 64 electrodes for patients 1 to 3). Note that, the channels are cluttered, and position of each channel is unclear (channel number or location cannot be used for feature extraction). In addition, each electrode has a diameter of 4 mm. Signals from each electrode separately recorded and then normalized to the range in the period, as the data stored contest. Signals sampling with a rate of 1000 Hz and frequency components less than 0.15 and more than 200 Hz have been filtered.

2.2 Test Protocol

In performing this test, a monitor is located near the patient's bed, which displays the name of each finger on it, is a sign for the patient to move his fingers. Each symptom lasts two seconds. During this period, the person should be 3 to 5 times bending the finger shown (bending frequency proportional to the finger and samples changed). After each sign, two-second interval to relax the patient in that time, the monitor is black, and there is no sign on it. This test in total 10 minutes (600 seconds) it takes, during which the shaking a finger command is shown 30 times a total of 150 signs (90 to 150 times bending for each finger). The signs are shown randomly. Studies have shown that physiologically, the fourth finger of each of the third and fifth fingers shake and so even though its information located on data collection but not used in calculations and useful (fingers orders is such that the thumb is considered the first finger). Places of the finger are determined by the specific gloves. The signals by sensors gloves are recorded by which we could understand each finger every time were moved.

2. 3 Data structure

Overall, the data structure is such that the data related to each person is stored in a separate file. This file is variable in three categories:

Train_Data: this set, 2.3 beginning of recorded data from the ECOG as is the time x channel. That includes 400,000 samples per channel (40 seconds with a sampling rate of 1000 Hz).
Train_dg: this set, 2.3 beginning of recorded data by special gloves containing data of finger placement and for time x Channel and has 400,000 samples for each finger.
Test_Data: This collection includes the remaining 1.3 of the data is recorded in ECOG (200,000 samples per channel). The set to predict the movement of fingers in remaining time is used.
Also, Test_dg set which contains the remaining 1.3 of the data recorded by special gloves and contain information about the movement of fingers in the time remaining (200,000 samples for each finger) and is used to evaluate the results after the contest is available to everyone.

2.4 How to evaluate the results

Per subject, in the remaining time (200 seconds) a vector 50 samples obtained including forecast move five fingers in 4-second intervals. The vector with the main vector that is obtained from test_dg signal which includes fingers movement signals compared and accuracy coefficient between these two vectors as an accurate measure of the prediction will be accounted.

3. Implementation

In this part of the classification process, related signal to move the fingers explained. First, basic processing steps will be explained. Then, the type used features and reduction method of features, as well as classification method, will be described. In this study, only data of the first patient was used.

3.1 Preprocessing

Preprocess included four sections of removing the noise power, brain signal smoothing of the brain, choose a suitable frequency range, and amplitude modulation method is applied. For selecting suitable frequency ranges that have the greatest and most useful information to move fingers, previous work by the researchers was used ((Pakravan. 2010), (Bougrain, 2009) and (Jaime, 2016)) and the frequency ranges 60-100 Hz, and 100-200 Hz were selected as the best frequency range. Frequency partitioning by Betterworth pass filter with 9 degrees done that this action was done in Matlab. With reference to the research work carried out by the winners of the contest BCI2008, a signal from the primary brain signals made that it was one-fortieth of the original signal, but the basic signal information has not gone, and new signal still has high-frequency components.

This type of processing technique, known as amplitude modulation has been named by contest winners (Bougrain, 2009). For this purpose, at intervals of 40 milliseconds, the brain signals used is about 1.

$$x(t_n) = \sum_{t=0}^{\Delta t} v^2(t_n + t)$$

This type of modulation, as the sum of powers of brain signals in intervals of 40 milliseconds and in intervals of 40 milliseconds, in the signal energy will be logged. In this regard v domain samples of brain signals, $x(t_n)$ is n new samples in the range of 40 ms and Δt also is time 40 ms. In order to smoothing signal, a filter was used (Rizon M, 2010):

$$X_{new}(t) = X(t) - \frac{1}{N}\sum_{i=1}^{N} X_i(t)$$

In the above equation, N is the number of brain channels. As well as to eliminate the noise power (60 Hz) which greatly affect signal-processing operations, is also a notch filter was used.

3.2 Selecting proper time range to brain signal partitioning and select the starting point processing

As already mentioned in the introduction of research data, any sign that lasted 2 seconds and 2 seconds is also intended to relax. Therefore, it seems that the brain signals divided into intervals of 2 seconds. But this can only be the best results that person in the whole signal recording time (600 seconds), law 2 seconds movement and 2 seconds of relaxing is observed. But the fingers signal observed otherwise. This means that in most movement ranges, person more than 2 seconds of movement or movement is done in the period of relaxing. This can be seen in Figure 1. As you can see in the figure, person in three 4-second ranges, the finger movement has continued. So in order to achieve a better result, instead of the signal partitioning to 2-second intervals, total 4-second range as a range of finger movement was considered and four seconds intervals associated with each class from 1 to 5 was assigned to first to fifth fingers.

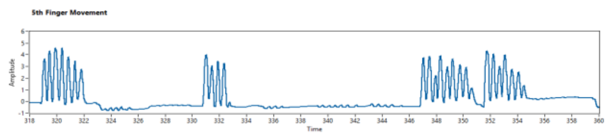

Figure 1: Fifth finger signal for first person

One of the parameters in enhances the classification accuracy of brain signals has high importance is determining the beginning time of signal processing.

Because if not set correctly this time, according to the wrong time shifts in brain signal segmentation created, the output accuracy of classification greatly reduced. By observing fingers signals related to the patient, the upper approximation can be said that starting movement was in the third second. Therefore, segmentation of brain signals, starting from the third second of data record was done. As shown in Figure 2, the first movement related to the fourth finger and from 3 seconds onwards has been done.

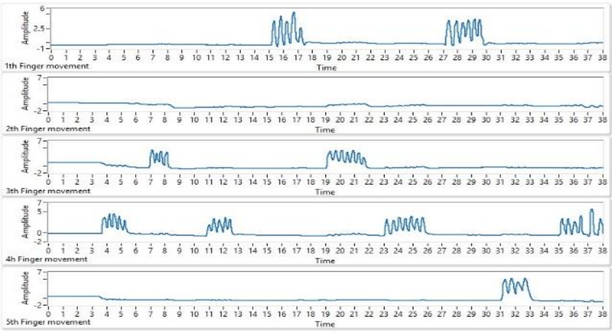

Figure 2: Fingers signal for first person

3.3 Appropriate feature selection

To determine the best features, previous work carried out in the field, and following features were extracted from brain signals.

1. Energy in frequency bands 60-100 Hz and 100-200 Hz.
2. Frequency features depends on the frequency conversion DCT include 6 first components transforms in frequency bands 60-100 Hz and 100-200 Hz

3.4 Features Reduction

In this study, methods for reducing features used, including using PCA to reduce the size of features and Rough theory was superior method for selecting channels. The idea of rough set theory was according to research in the field of BCI's and also the theory to issues such as reducing features, to improve the accuracy of classification and.... is used (Su, Y., Dai, 2010), (K. Liao, 2014), (Kaya, 2013). One of the important properties of extracted features is that all features are numerical. In order to apply rough set theory on the set of features, first of all, the discrete operation must perform. In this study, from discretization was used based on the highest resolution. Details of the method and its mechanism in the RSES software in (Vogel, 2015) are given. Channels that were selected as a result of the above methods, 9 channels are included 1-2-4-7-20-36-39-43-52 channels.

3.5 Classifiers

In this study, the neural network classifier in 5 class's mode as well as for first time adaptive neuro fuzzy inference system to assess the network capability in existing data classification project and artificial neural networks were compared with the results obtained by above favorable method. The neural network classifier of neural networks toolbox in Matlab was used. For this purpose, the preparation of training vectors and classes -related vector, these vectors as input to pattern recognition system entered from the neural network toolbox. The 100 neurons in the hidden layer with sigmoid training function were used. In continued research, with emphasis on the use of adaptive neuro fuzzy inference system classified in the available data, it has been studied in more detail.

3.5.1 Adaptive neuro-fuzzy inference system (Anfis)

In general, a fuzzy system of fuzzy-making processes, fuzzy foundation law is fuzzy and non-fuzzy output engine. In the fuzzy step, each component of input data, convert into a membership degree. In the classic set, membership functions is two members set zero and one, while the range of fuzzy membership functions is closed between zero and one. Direct perception, inference, genetic algorithms and neural networks are such ways that can be identified membership function of variables. Commonly artificial neural networks to optimize fuzzy membership functions used. This method is called adaptive neuro fuzzy inference system following is introduced.

Adaptive neuro-fuzzy inference system (Anfis) first time in 1993 by Zhang (1997, 1993) was introduced. The system of neural networks and fuzzy logic algorithms for designing nonlinear mapping between input and output space is used. The system of fuzzy system language power with numerical strength of neural network in the modeling of complex processes is very powerful. The more complex training algorithm that uses a combination of gradient method for reducing and minimizing squares, introduction and implementation and rapid learning system equivalent to the fuzzy inference algorithm is discussed. If a fuzzy inference system with two inputs x and y and one output z presented. The first order Sugeno fuzzy model with two if-Then fuzzy law can be expressed as follows:

$$Rule1: if\ x = A_1\ and\ y = B_1\ then\ z_1 = p_1x + q_1y + r$$
$$Rule2: if\ x = A_2\ and\ y = B_2\ then\ z_2 = p_2x + q_2y + r$$

The first layer (input): each node i of this layer, membership values that belong to each of the appropriate fuzzy sets, using the membership function produced.

$$O_{1,i} = \mu_{A_i}(x) \quad for\ i = 1,2 \quad or \quad O_{1,i} = \mu_{B_{i-2}}(y) \quad for\ i = 3,4$$

Where x (or y) node input ith and A_i (or B_{i-2}) is language tags (like "small" or "large") are related to the node. $O_{1,i}$ is membership of fuzzy set (A1, A2, B1, B2) and determines the degree to which input variable x (or y) correspond to the A quantity. Usually, membership functions A, B by bell functions is expressed:

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}}$$

The second layer (membership functions input): This layer is composed of Π node as an input signal, and the output is multiplied. for example:

$$O_{2,i} = w_i = \mu_{A_i}(x)\,\mu_{B_i}(y) \qquad for\ i = 1,2$$

In other words, the operator layer "and" used.

The third layer (law): each node in this layer is a fixed node N is labeled.

The i-th node have the ability to fire law ith to the ability to fire calculated and for convenience, the outputs of this layer is called the ability to normalized fire.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2} \quad , \quad i = 1,2$$

The fourth layer (membership function output): nodes this layer match function nodes:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i)$$

Where $\bar{w}_i$ third layer is output and p_i, q_i, r_i is parameters set. These layer parameters are like the parameters set of Tully fuzzy model.

The fifth layer (output): This layer is called fixed node Σ, overall output is calculated by adding up all input signals. So in layers defuzzification process, the results of any fuzzy law convert to defuzzification output.

$$O_{5,i} = \sum_{i=1} \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

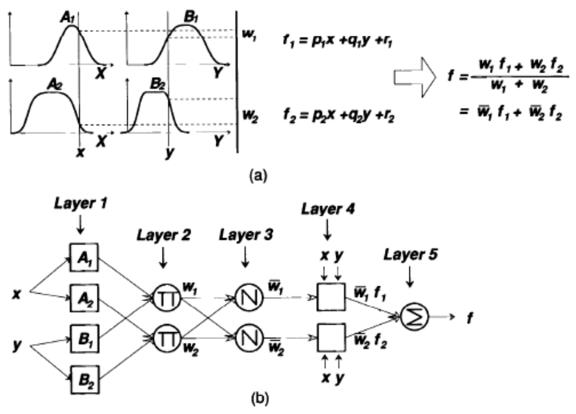

Figure 3: Sugeno first order fuzzy model with two fuzzy law and ANFIS equivalent system

Neuro-fuzzy model allows fuzzy systems on parameters education issues use adaptive returns training algorithm. The downward sloping algorithm error, the error correction parameters are distributed to the inputs. In this method, using the error retarder algorithm, the error value is distributed to the inputs, and the parameters are corrected. This training method is exactly the same as the post-propagation technique used in artificial neural networks. The neuro-fuzzy network structure is observed in Figure 3, the total output (f) as a linear combination of parameters written as follows:

$$f = \frac{w_1}{w_1+w_2}f_1 + \frac{w_2}{w_1+w_2}f_2 = \bar{w}_1(p_1x+q_1y+r_1) + \bar{w}_2(p_2x+q_2y+r_2)$$
$$= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 +$$
$$(\bar{w}_2 y)q_2 + (\bar{w}_2)r_2$$

The implementation of a fuzzy system is done in a way that will have the ability to learn. Then parameters values obtained using the least squares error method. By combining these techniques and error retardation method, creating a blended learning method that works as follows:

In both training when moving forward, outputs of nodes are calculated as normal until the fourth layer, and the resulting parameters are calculated by methods such as least square error are calculated.

In the following, after calculating the error in the afterward return, the error ratio is distributed over the conditional parameters and corrected by using the error retardation method are corrected.

3.6 Evaluation criteria for classification and accuracy of classification

The criteria used in this study to obtain classification accuracy, is confusion matrix or cross matrix. The following equation was used to calculate the classification accuracy (Vogel, 2015):

$$\%ACC = \frac{\sum_{i=1}^{M} n_{ii}}{N} * 100$$

In this regard, M is the number of classes and N is the number of total signs and n_{ii} confusion matrix elements are disturbed.

3.7 The final results of the fingers movement classification

In order to find the best number of features and the best features and evaluation of classification performance, cross validation was conducted to assess stage. On the classification of neural network of training data, 70% as training- training, 15% as training-evaluation data to improve internal network parameters during training and 15% as training-test data were considered. Adaptive neuro fuzzy inference system were divided training data into two parts training- training with 69 samples and training- test 30 samples and 5 data categories with different samples were generated randomly. As a result, classification with neural network with the frequency characteristics of DCT and the use of selected channels using the Rough theory and feature size reduction by PCA can see in Table 1 in the form of the confusion matrix, and the average accuracy of 77.6% is obtained for the five fingers. The use of neural network classifiers 100 neurons in the hidden layer and also 4 features were used.

Table 3.1: Classification results on the fingers after practice neural network model on test data in the use of Rough and PCA.

		target class				
		1	2	3	4	5
Output class	1	12	0	0	0	0
	2	0	11	1	0	0
	3	0	0	5	4	1
	4	0	0	0	3	0
	5	0	0	0	5	7
		100%	100%	83.3%	25%	87.5%
100-200 Hz frequency band and characteristics of DCT						

Classification result with adaptive neuro fuzzy inference system with frequency DCT features and use of selected channels using Rough theory and feature dimension reduction by PCA in Table 2 can see in the form of confusion matrix that the average accuracy of 89.9% is obtained for five fingers. In the adaptive neuro fuzzy inference system of 29 clusters in primary fuzzy model and 4 also features were used.

Table 2: Classification results for fingers movement after practice Adaptive Neuro Fuzzy Inference System models over the test data in the use of Rough method and PCA.

		target class				
		1	2	3	4	5
Output class	1	12	0	0	0	0
	2	0	11	0	0	0
	3	0	0	6	0	1
	4	0	0	0	10	2
	5	0	0	0	2	5
		100%	100%	100%	83.33%	62.5%
100-200 Hz frequency band and characteristics of DCT						

Conclusions

The aim of this study is to predict the movement of fingers using brain signals processing that the data used was related to the fourth series of BCI2008 tournament data. In the implementation, the best results for classification of brain signals at a frequency of 100-200 Hz and the characteristics of DCT, and using classification of networks of adaptive neuro-fuzzy inference system were obtained.

Of course, in this regard, using rough set theory played a significant role in choosing the best channel. These results include classification with average accuracy was 89.9% for all fingers. To improve the classification results, a combination of genetic and fuzzy algorithms and PSO to improve the fuzzy model parameters used.

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