Selecting and Extracting Effective Features of SSVEP-based Brain-Computer Interface

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Abstract

User interfaces are always one of the most important applied and study fields of information technology. The development and expansion of cognitive science studies and functionalization of its tools such as BCI (Brain Computer interface), as well as popularization of methods such as SSVEP (Steady State Visual Evoked Potentials) to stimulate brain waves, have led to using these techniques every day, especially in appropriate solutions for physically and mentally handicapped people. Computer- brain interfaces enable users to communicate without involvement of their lateral muscles and nerves and since these interfaces are not dependent on muscular nervous control, they enable people with muscle neuromuscular control disorders (such as amyotrophic lateral sclerosis, brain stroke, cerebral palsy, etc.) to control and communicate. The main idea in this research is the implementation of a proposed system to provide the best options to the user due to the limitations of the simultaneous options in the SSVEP method and the specific user conditions for disabled people. To do this, we present a new implementation method based on extracting the wavelet feature and then dimension reduction by PCA (Principal Computer Analysis) and after the extraction step, the features are classified by the SVM (Support Vector Machines) and KNN (k-Nearest Neighbor) classifiers. It has been observed in this project that99.3% accuracy can be achieved by KNN classifier.

Keywords: Electroencephalography, Evoked visual Potential, User Interface, Brain-Computer interface

1. Introduction

Brain- Computer Interface (BCI), also known as the Brain- Machine Interface, refers to the direct relationship between the brain and an external mediator. These interfaces, as their name implies, send brain signals directly to the computer without touching the computer or using the mouse and the keyboard by the user. These interfaces have different types, and the way they are used is consequently different. The brain- computer interface system analyzes brain signal systems to generate control commands for computer programs or external devices. Brain- computer interfaces as an alternative communication channel are able to help people with severe motor disorders to communicate with the environment and participate in daily life activities. People with disabilities in all age groups can benefit from such brain-computer technologies [1]. These days, equipment related to brain- computer interfaces needs to be carefully thought and studied because the future of different sciences is surely moving toward the point where using different applications of this field is required. New research focuses on non-invasive methods. This method is completely different from traditional and old methods. In traditional ways, it was required to implant a chip or electrodes in the human brain, which is referred to as an aggressive method. This method is now less used because it needs a lot of equipment and space to control the health of the living tissue of the brain where the device is embedded.

A brain-computer interface is a technical system that applies actual patterns of brain activity in real-time to transfer them to the control commands for computers or external devices [2, 3]. It is also a combination of various sciences such as electronics engineering, computer engineering, medical engineering, neuroscience and psychology. Brain- computer interface applications can help people with diseases caused by disorders such as cerebral palsy, spinal cord injury, stroke, amyotrophic lateral sclerosis ALS(Amyotrophic Lateral Sclerosis), or muscular dystrophy to engage in daily activities. These disorders can be found among all age groups. Also, the effects of aging alone create physical constraints that often cause the elderly people to have trouble communicating with their environment. Although the special needs of all age groups throughout the development of the brain and computer interface should be taken into account, most of the brain-computer systems are tested with younger people. However, an effort has been made to conduct population-based studies. Several brain- computer interfaces have been tested in real scenarios [4, 5].

In fact, very soon the day will come when human beings can only and only use the power of their minds to do things; which was a dream before and the writers of scientific-fiction stories did not dare to write about many of them. Different methods are presented to measure the brain activity, procedures and formatting, among which Electroencephalography or EEG (Electroencephalography) is currently the most popular method of measuring brain activity for the design of a brain-computer interface. Stable state visual evoked potential (SSVEP) represents a specific type of user's brain activity which appears in the occipital area of the brain when the user stares at a flashing optical stimulus at a frequency of 6 Hz. Accordingly, a signal with the same frequency can be recorded in the occipital area of the brain and a brain-computer interface system designed using that. To do this, you need to separate the different classes of these signals and assign each one a command.

A strong correlation has been observed between the precision of the brain- computer interface and the length of time assigned to the SSVEP classification in EEG analysis .In general, a short time window will lead to classification errors and a long time window reduces the function of the brain- computer interface. In many practical experiments with subjects, it became clear that some users (especially the elderly people) need to look at the goal stimulus for a relatively long time; therefore, a long time window is needed to achieve control of the brain-computer interface system [6]. Due to the low signal-to-noise ratio in this system, pre-processing and noise reduction operation will be initially performed on these signals.

The next step is the extraction of a feature in which the frequency information and time information of the EEG signals are extracted using various time-frequency analysis methods.

2- Reviewing Previous Works

Brain electrical signals for Electroencephalograms were first recognized by Dr. Hans Burger in the year 1920. Subsequently, an investigation was conducted to identify the fluctuations of the brain signals that led to the identification of alpha waves. In 1974, Gary Walter introduced the first prototype of a brain-computer device that was based on imagining a power key (on-off key bottom) [7, 8]. In 1998, Philip Kennedy founded the new brain mapping approach. He was the first person who implants the interface tool in the human body. Although this tool had limited applications, it could have given future researchers the courage to make possible many impossible things in the world of science. Philip Kennedy's research later became the basis of the construction of wireless electrodes, which is widely used in the field of brain- computer interfaces. John Douglas and the team under his supervision, in 2001, first developed the BCI model, calling it “the brain gate”. Their first commercialized product was named "Neural Networks" sponsored by a company. The Research and Development Center of Colombia University was able to successfully record and observe the electrical activities of the brain with higher precision. The reports of researchers who used this tool indicated that the electrical waves emitted from the brains of the patients can be detected with a high accuracy before an epileptic attack happens. In June 2004, Matthew Nigel recorded his name in the brain- computer interface history by implanting this tool in the human body. In December 2004, Jonathan Wolpaw and researchers at the New York Health Center conducted a new study on the brain and computer interface that showed how to use computers by using brain and machine interfaces. In this study, patients were asked to put an electrode-covered cap on their heads and the device recorded their motor cortex signals. This study was a major step in improving the various diseases caused by damages to them by moving motor.

This type of systems helps people who are not even able to move their hands or fingers. In this case, it is very important and necessary to perform various actions using the thinking or movement of the eye on the screen. With the advancement of these systems, various applications can also be imagined for ordinary people; applications such as doing personal activities when the focus is on other activities and the moving parts of the body cannot be used in these situations. One of the most commonly used methods for commercializing these systems is the creation of computer games and virtual world control based on the brain- computer interfaces [9, 10].

Mr. Shyu et al. (2010) used the SSVEP feature to implement the brain- computer interface (BCI) system. Their proposed system was built with a LED simulation panel, a medical signal processing circuit and a real-time signal processor based on the

Field Programmable Gate Array (FPGA[8]). Their design is different from other BCI systems, and uses Electroencephalogram (EEG) measurement equipment, personal computers and real-time commercial signal processing software. Their proposed system allows users to use their brainwaves to communicate with the external world. The implementation of the prototype of the SSEVP-based brain- computer system interface, FPGA, confirms the proposed efficacy. Their proposed system has obtained a transfer rate of 24067 bits / min for normal topics [11]. Friganovicand and his colleagues (2016) developed an SSVEP-based brain- computer interference system. They offered a small, portable system that uses only a dipole channel. They used 3 LED chess boards to control simple software for turning the lamps on/off, which can be easily implemented at home. They suggested that in the future, the focus is on improving the frequency calibration for each subject and any classification of machine learning to improve strength and accuracy [12].

Long and his colleagues (2012) presented a brain-computer interface by combining the rhythm of μ /β, which resulted from the P300's motor imagery to control the speed and direction of a wheelchair simulated in virtual environment. Their work has led to improving the accuracy and presentation of several independent control signals. They suggested that additional signals can be used for the computer-brain interfaces system to control the wheelchair [13]. Peng et al. (2016) presented a smart system for nursing beds which is controlled by a hybrid brain-computer interface and relies on P300- based system-brain switch. This system has a satisfactory function in deciding the ideal state of control. The proposed system has a precision of 75.93%. The disadvantages of their work were that the S5 and S8 had less control accuracy (80%), and S2, S4, S5 and S8 mistakenly activated the P300-based brain- computer interfaces during the rest periods. Brain switches are designed using a key-based method [14]. Davlea and Teodorescu (2011) addressed the modular implementation of computer- brain inter face based on the SSVEP pattern. The goal of modular hardware and software design is to achieve the flexibility and compatibility required for a real-life applied system. Dual-channel computer-brain interfaces are developed based on sensible modules and embedded processors.

3- The Necessity of Research

User interfaces have always been one of the most important study and applied fields of information technology. This has led software and hardware manufacturers to implement graphical user interfaces as well as new controllers on their agenda. The development and expansion of cognitive science studies and functionalization of its tools such as BCI, as well as popularization of methods such as SSVEP to stimulate brain waves, have led to using these techniques every day, especially in appropriate solutions for physically and mentally handicapped people. EEG is a neuronal imaging technique used to measure disturbances that occur inside the brain due to electrical activity in the brain. This is a unique technique that can be used to connect the human brain to the outside by electrical signals generated from the EEG device. These electrical activities inside the brain are generated by physical or mental activities to control the intended object [15]. These signals are collected by the outer layer of the brain i.e. the scalp. The electrodes are placed on the scalp and collect the brain signals [16]. This type of data collection may be accompanied by disturbances such as motion noise, etc. Therefore, after collecting signals, these noises are eliminated. The Brain and Computer Interface (BCI) was designed to establish a direct connection between the brain and the device.

This interface receives and recognizes the wishes of individuals through the EEG signal. Today, various research groups are working to help people with diseases such as MS (multiple sclerosis), ALS (Amyotrophic lateral sclerosis), etc. in the field of brain and computer interfaces. Brain- computer interfaces enable users to communicate without involvement of their muscles and lateral nerves. In this work, a SSVEP-based brain-computer interface is provided. When a flashing stimulus is displayed at a constant frequency and greater than 5 Hz, the brain's signal that is EEG, is collected by electrodes and recorded by the device. In fact, this flashing stimulus causes an increase in the energy of the same frequency spectrum from the EEG signal in the occipital region (the vision region) [17]. The visual evoked potential is a biomechanical signal from cylindrical and conical optical receptor cells that provides information from the visual system and can be transmitted through the ganglion cells and the optic nerve to the cerebral cortex and recorded on the visual cortex area. Contrast sensitivity is one of the factors affecting VEP (Visual Evoked Potential). The main idea in this research is the implementation of the proposed system to offer the best options to the user due to the limitation of concurrent options in the SSVEP method and the specific user conditions for incapable people. To do this, we presented a new implementation method based on extracting the wavelet feature and wavelet then PCA and after the feature extraction step, we assign the extracted features in each step to classifiers such as SVM and KNN for the data categorizing. Finally, it is examined that which classifier is more appropriate for classification of SSVEP-based brain and computer interface systems signals.

4- Research Method

The main idea in this research is the implementation of a proposed system for the SSVEP-based brain-computer interface for specific user conditions of disabled people. To do this, we present a new implementation method based on the feature extraction by wavelet (wavelet transform) and the reduction of the data dimension obtained from the previous step by the PCA and after the feature extraction step, classifiers such as SVM and KNN are used to classify the data. Finally, it is examined which classification is more appropriate for classification of SSVEP-based brain-computer interface system signals. The general method of doing this is to first perform Brain signal sampling using EEG-based open BCI device. After obtaining EEG signals, the data are first divided into 10-second frames. And after the new data set was created with 19 electrodes, noise from blinking and muscle movement and urban electricity noise is extracted by fast Fourier transform or FFT and deleted with a band- pass filter with a frequency of 2 to 30 Hz .Then the features of each frame and each electrode were extracted by the wavelet method, wavelet then PCA and dimension reduction. After selecting the effective features in the work, all the data from the feature extraction step is divided into the test data and training data by the K-Fold method. These data are then assigned to the two different classifiers of SVM and KNN for testing. Finally, by examining the results obtained from two classifiers, it is determined that which one is better in the SSVEP based brain-computer interface system. The diagram of the method is shown in Fig 1.

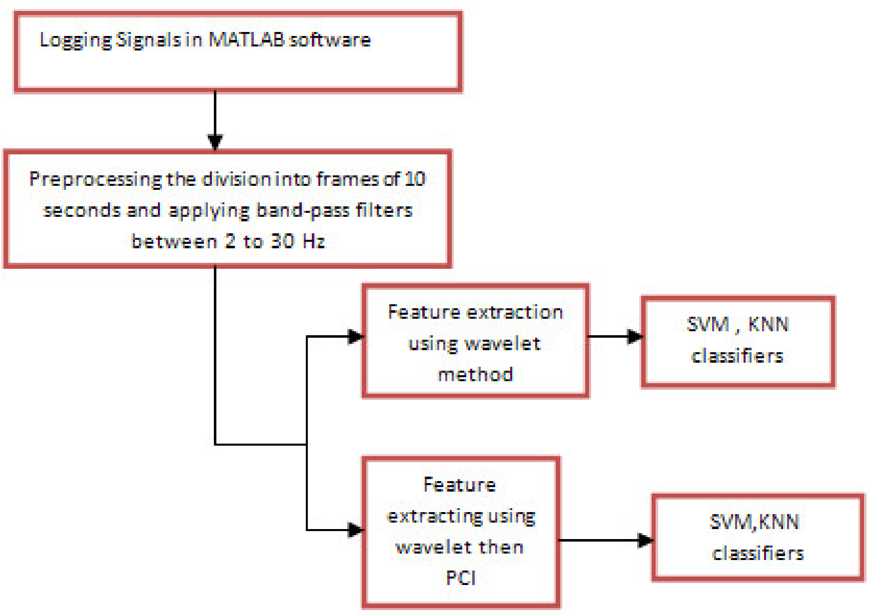

Fig.1. The general method of work

The data used in this study was taken from the reference [18]. In this work, the frequency response of SSVEP for 32 frequencies (5-84 Hz) and the dynamics of response time of the brain at 8, 14 and 28 Hz were examined to determine the desired neurophysiological parameters and to be described for the start delay and other SSVEP stimulus constraints in applications such as the BCI system. Data is collected for each individual at three frequencies of 8, 14 and 28 Hz. This was done in five rounds.

A total 15 data is recorded for each person. The sampling rate in this dataset is 256 Hz.

In figure 2 the location of the electrodes on the head to record the EEG signal in the desired data set is presented.

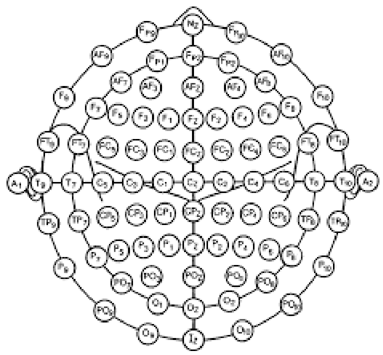

Fig.2. Electrodes on the head to record the EEG signal

According to the studies, a set of 19 electrodes that were used in past works were separated from these 128 electrodes and were considered as the main electrodes of our work (Table 1). Signals recorded by these 19 electrodes were considered as inputs.

Table.1. The desired electrodes and their equivalent in the 10-20 system

Electrode No	System 128	System 10-20
19	A19	PHz
17	A17	PO3
30	A30	PO4
15	A15	O1
28	A28	O2
23	A23	Oz
5	A5	P1
32	A32	P2
21	A21	Piz
1	A1	Cz
119	D23	T7
58	B26	T8
39	B7	PO8
108	D12	FC3
63	B31	FC4
110	D14	C1
52	B20	C2
7	A7	P3
36	B4	P4

4-1 Results from two classifiers of SVM and KNN on two sets of data

Now we examine the results of two classifiers on two extracted data sets only with a wavelet and a wavelet dataset, then PCA. It can be seen that by the KNN classifier, the classification of the wavelet dataset is faster than the other two datasets.

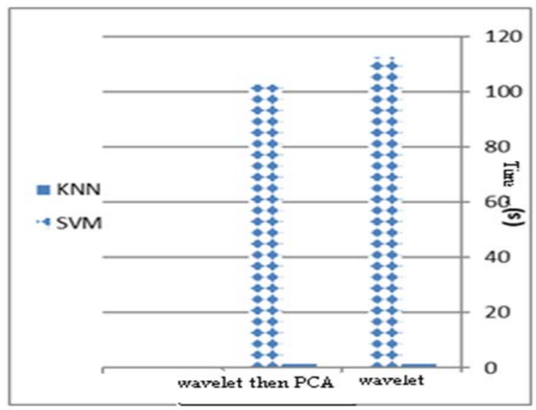

Fig.3. Comparison of the implementation time of two classifiers of SVM and KNN on two types of data sets

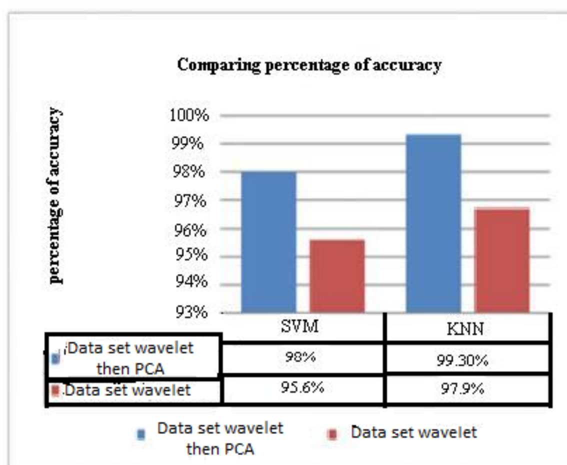

Fig.4. Comparison of the accuracy of two classifiers of SVM and KNN on two types of data sets

In the diagram below (Figs 3,4), the overall comparison of two KNN and SVM classifiers with two data sets i.e. the extracted dataset, is given only with the wavelet of the wavelet dataset, then the PCA.

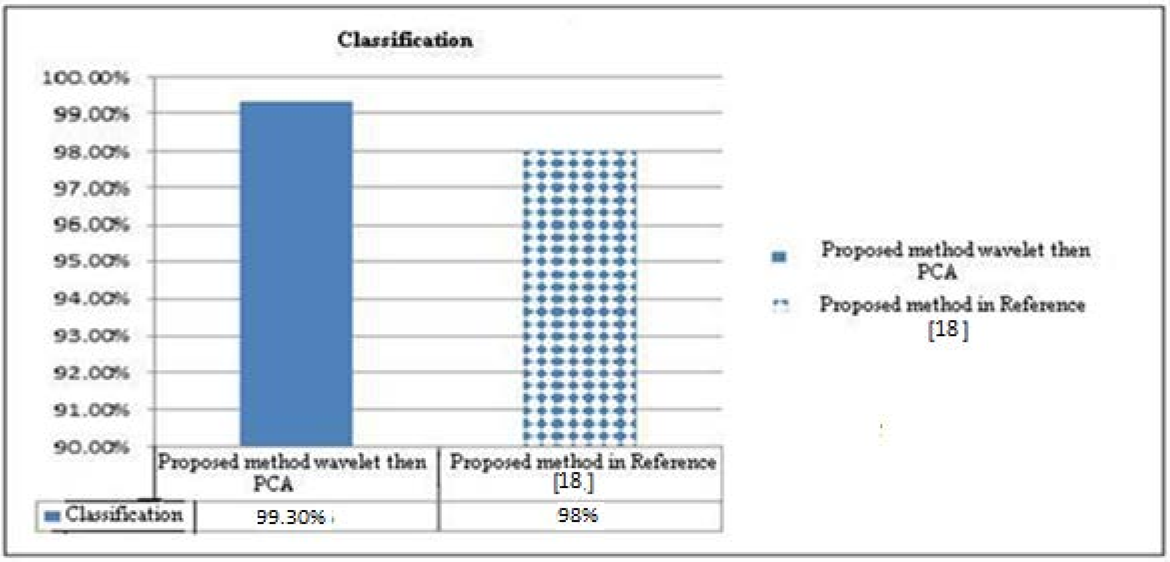

Fig.5. Comparison of the accuracy of our system with the method [18]

4-2 Comparison with previous work

In this section, we compare the highest accuracy obtained by our method with the accuracy obtained by [18] which had used our data set (Fig.5). It can be seen that the combination of the wavelet feature extraction then the PCA with the KNN classifier outperforms the classifications of the work performed in [18] in terms of classification accuracy.

Conclusion

To demonstrate the ability of the proposed method, this method was applied to the data set in MATLAB. The results obtained from the two classifiers of SVM and KNN were analyzed and then the parameters obtained from each of them were compared. It can be observed that by the KNN classifier, the classification of the wavelet dataset is faster than the other two datasets. Also, in comparison with the work performed in [18], the combination of extracting the wavelet feature and then the PCA with the KNN classifier resulted in better results for the classification accuracy. According to research, the following suggestions can be made:

a) In this research, our proposed method was tested on three frequencies 8, 14 and 28 Hz. This can have a limitation on the options required by the users. Therefore, this method can be tested on several other frequencies for different target options.

b) Implementation of the proposed system on a true and suitable application, such as smart home.

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