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EEG Wave Identification in Human Brain with Emotiv EPOC for Motor Imagery

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Abstract

Brain Computer Interfaces, abbreviated as BCI, is a technology which allows users to take action in computer by focusing on which action the user wants to do. BCI processes brainwave which recorded by means of electroencephalography so it is can be known to computers. Inside the brain, nerve impulses is passed across corresponding nerves to command body part into action, as a result, the respective body part responded with the action that brain commanded. This chain of events can be harnessed by BCI so that brainwaves can be acquired. Using a proper classification method, brainwaves data can be used as a digital command to computer, eliminating the need of actual real-world action to act in a computer. One of the BCI's interesting topic is Motor Imagery, a topic which deeply examine brain activity when imagining motoric activity such as moving left hand. Brain activity is recorded by electroencephalography so that BCI can use the data as a reference to translate brain activity into actual motor activity or as computer trigger. Emotiv EPOC is one of the common BCI distributed to public users. The purpose of this research is to determine how BCI can identify and distinguish human's brainwave when performing different activities. Emotiv EPOC is used in this research with a purpose of whether Emotiv EPOC can be used for Motor Imagery. A simple method is used in this research, using Graz BCI scenario provided in OpenVibe installation bundle and then assess the test results with 5 seconds timeframe. A total of 6 scenarios is used for testing purpose. The success rates of those 6 scenarios are: scenario 1 with 76,67% success rate, scenario 2 with 91,67% success rate, scenario 3 with 28,33% success rate, scenario 4 with 13,33% success rate, scenario 5 with 60% success rate, and scenario 6 with 76,67% success rate. The result from this research indicates that Emotiv EPOC can be a possible option but not recommended for implementing motor imagery application.

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Keywords: Brain Computer Interfaces, Electroencephalography, Motor Imagery, Brain Waves

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1. Introduction

All activities in form of communication and control require nervous and muscle coordination. The activity process starts from the intent of the subject, then the intent triggers several parts of the brain to send signals to the body part. The body part then responded with action [1]. EEG acquisition device is useful for recording EEG signals from the brain obtained from the scalp or the surface of the brain, indicating the neural activity in the brain [2]. To get EEG signals, EEG device uses recording electrode which signal is amplified and digitized [2].

A study shows that EEG-based BCI can control robotic prosthetic hand with 82.5% accuracy in first session, 88.75% accuracy in second session, and 90% accuracy in third session [3]. This finding proves that BCI can translate human's intent into actual action. It also proves that computer can distinguish EEG signal related to certain activity among others. In order to translate human's intent, BCI should be intensively trained for each user first [4]. Even though the BCI is properly trained, BCI usage still requires user's special skill that need to get used to it [2].

A Research conducted by Fabiani in 2004 stated that, human's brain activity which indicated by EEG signal bursts, actually can move mouse cursor in computer with BCI [5]. This study showed that the BCI has been able to translate human's intent into action in computer. It is not impossible that further research can enhance BCI usage into something more complex, thus requiring advanced technology from the future.

EEG signal which is emitted by human's brain is a mixture of all thoughts of activities, mood, and other feeling [6]. It is very difficult to translate human's intent if there is not much reference data [2]. Oftentimes, other than EEG-based acquisition devices is required to get much more reliable data such as ECoG, NIRS and many others [2].

Yazdani et. al., stated that EEG signal is different across humans, although they are thinking the same thing [7]. That statement shows that EEG-based BCI gives different performance to different users.

The purpose of this study is to know whether Emotiv EPOC can identify and distinguish brain waves for Motor Imagery.

2. Definitions and Explanations

2.1. Brain Computer Interface

Brain Computer Interface is an artificial system that enables computer to directly receive order from human's thought in form of brain waves without using natural peripheral nerves [1]. Brain Computer Interface enable handicapped people to interact with their surrounding because Brain Computer Interface gives direct path from brain to computer. Figure 1 illustrates that Brain Computer Interface directly translates human's thoughts into action, without using natural neuromuscular pathways.

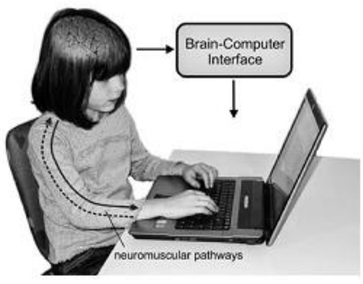

Figure 1 BCI as a new way of interaction [1]

Currently, Brain Computer Interface can access information with speed up to 22.85±1.85 bits/min [8]. That limited speed is heavily useful for brain-damaged people because it enables them to interact easily with their surroundings although constrained by limited ability of brain computer interface and limited response speed [2].

Brain Computer Interface has many usefulness, from entertainment or medical perspective. Some of that usefulness are: game controller, wheelchair controller, hearing aid device, prosthetic robot arm controller and many others [2][3][5]. With these vast potency, further research about Brain Computer Interface and its potency may lead mankind to future glory.

2.2. Electro Encephalogram

All form of activity in human's body need an order from brain, and nervous system to carry that order into respective body parts [1]. That brain order can be tapped in form of signal by brain waves acquisition device. One of those signal is Electro Encephalogram (EEG). These EEG signals can be acquired from electrical activity that happens on scalp. This activity of acquiring brain waves from the scalp is called Electro Encephalography [1].

EEG can be combined with Brain Computer Interface in term of doing something in computer. But, intensive training must be conducted first before doing further activity with Brain Computer Interface, because Brain Computer Interface can only classify some pattern when it has some good references [1].

EEG-based Brain Computer Interface can lead into wider potency of human's brain and computer. With further research, EEG-based Brain Computer Interface can create a whole new paradigm in computer usage.

2.3. Emotiv EPOC

Emotiv EPOC is a device that mounted on the head which consisted of 16 electrodes to record brain waves by means of Electro Encephalography and send the data wirelessly, Figure 2 shows a perspective of the device. This device can be used into research or entertainment purpose. [9].

Figure 2 Emotiv EPOC [10]

2.4. OpenVibe

OpenVibe is an open source platform that can be use for developing Brain Computer Interface application [11]. This platform can be used by anyone regardless their ability to code a program.

This platform boast on its reusability and modularity feature, so that its users need only to reuse provided functions and build it in OpenVibe designer to make Brain Computer Interface [11]. Another reliable feature is portability [11]. With its resourceful acquisition device driver collection, user can use many type of acquisition device without developing their own driver [12].

Development of brain computer interface with OpenVibe can be done with included OpenVibe designer. OpenVibe designer allows user to set flow of logic in EEG processing, Figure 3 shows a glance of OpenVibe designer.

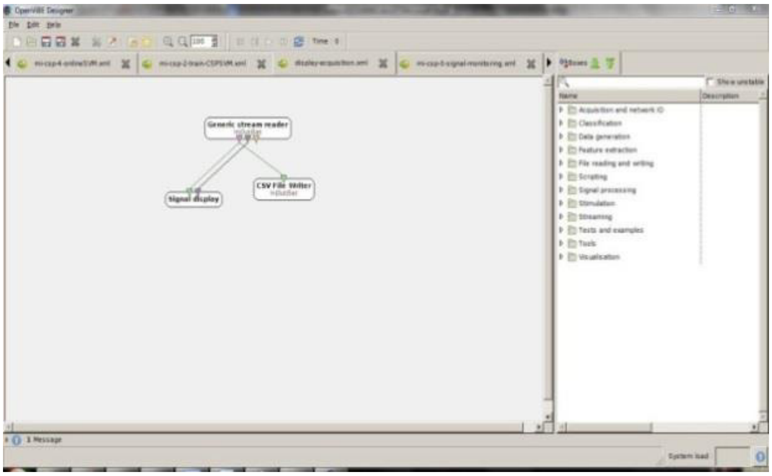

Figure 3 Screenshot of OpenVibe designer

3. Research Methods

3.1 Subject selection

Subject should be properly selected because Emotiv EPOC is designed all-size all-fit. Not all people have that all-size and all-fit head. Short-haired or even bald people also needed so that Emotiv EPOC's electrode can get a good contact with the scalp, resulting in good signal reception. However, even after adjusting Emotiv EPOC's electrode in many ways, it is still difficult to get a good signal reception evenly among the electrodes. Because of that, 10 greens or yellows in contact indicator is considered enough to continue research.

Selected subject is a student of Information System Department in Institut Teknologi Sepuluh Nopember. Subject voluntarily agrees to become research resource and can perform given task well. Emotiv EPOC device also well fitted onto subject's head, proven by good signal reception at each electrodes in numerous trial.

3.2 Data Acquisition and Classifier Training

This research is mainly focused on running Motor Imagery with CSP filter in OpenVibe. The first step in the scenario chain is Data Acquisition. EEG data is required as reference for Brain Computer Interface to translate brainwaves to virtual activity. In this step, only one subject used because every human have different brainwaves among others [13][7]. Other than that, this research is only an initial step towards broader purpose of motor imagery. Thus, this paper includes only one result. In future works, numerous subjects will be tested to broaden the results.

There are two activities to be trained, moving the left hand and moving the right foot. These activities is required to seek proof whether Emotiv EPOC can identifies and distinguish two different activities or not.

This step includes automatic CSP filter generation by one of the scenario inside the chain. CSP filter is useful for emphasizing the gap between one pattern to another. Then, next scenario to be run is Classifier Trainer, with data acquired as input, the scenario will read through the data while extracting feature vectors and write them all into one configuration file for later use. The classifying method used is Support Vector Machine (SVM).

3.3 Classifier Processor Testing

This testing step is executed by running mi-csp-4-online.xml in OpenVibe with adjusting simple dsp filter by x-0.5, simple dsp filter adjustment is required so that SVM classifier can process the value. The testing is performed ten times per activity in 30 seconds per session with 5 second timeframe. Each 5 seconds, it will be monitored whether the arrow on the visualization screen is pointing to the desired direction or not, if by 5 seconds the arrow is pointing to the desired direction steadily, then, that timeframe is considered successful. If not, then, that timeframe is considered a failure.

Testing Scenarios are:

1. Left Hand Movement
2. Right Foot Movement
3. Simultaneous Left Hand and Right Hand Movement
4. Simultaneous Left Hand Movement and Head Nodding
5. Simultaneous Right Foot and Left Foot Movement
6. Simultaneous Right Foot Movement and Head Nodding

The main scenarios in this research are scenario number 1 and 2. But, to find out if there is unique signal pattern in those main scenarios, so 4 additional scenarios which are consisting of combination between main scenario and additional activity were made.

4. Results and Discussions

4.1 EEG Data

Figure 4 shows EEG data acquired from acquisition step in line graph form. The graph visualize signal amplitude in each of Emotiv EPOC's electrode.

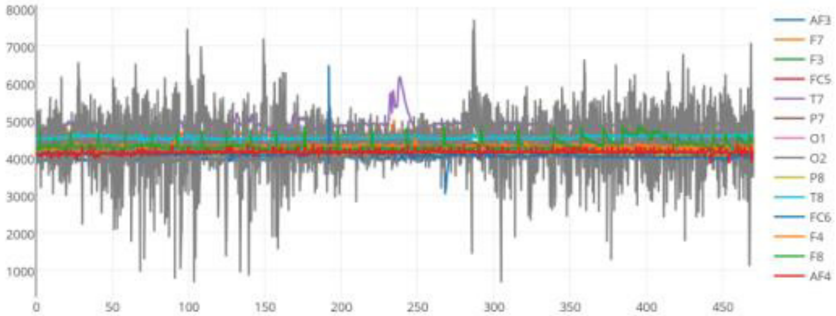

Figure 4 EEG Data Visualization

Each of the colours of the line represents one of the electrodes. The amplitude in each second is later extracted by classifier trainer to become feature vector, useful for SVM generation.

4.2 Test Results

All test scenarios have been performed and some of the result can be seen in Table 1. Value of 0 indicates failure and 1 indicates success. Value of no means number of test sessions.

	Timeframe					
no	5	10	15	20	25	30
1	0	1	1	0	1	1
2	1	0	1	0	0	0
3	0	1	1	0	0	0
4	0	1	1	1	1	0
5	0	1	1	1	1	1
6	1	1	1	1	1	1
7	1	1	1	1	1	1
8	1	1	0	1	1	1
9	1	1	1	1	1	1
10	1	1	1	1	1	1

	Timeframe					
no	5	10	15	20	25	30
1	1	1	1	1	1	1
2	1	1	1	1	1	0
3	1	1	1	1	1	1
4	1	1	1	0	1	1
5	1	1	1	0	1	1
6	1	1	0	1	1	1
7	1	1	1	1	1	1
8	1	0	1	1	1	1
9	1	1	1	1	1	1
10	1	1	1	1	1	1

Table 1 Test results from scenario 1 (left) and scenario 2 (right)

Scenario 1 test result have 76,67% success rate while scenario 2 test result get 91,67% success rate. The success rate is computed by calculating success event in all timeframes.

Scenario 3 test result have 28,33% success rate while scenario 4 test result get 13,33% success rate. From scenario 5 test result, calculation shows 60% success rate while scenario 6 test result get 53,33% success rate.

4.3 Test Results Discussions

In test scenario 1, SVM classifier processor is already able to classify online EEG acquisition in desired way, moving the left hand. Other than that, looking from increasing performance in each of the sessions, subject factor in imagining consistent motoric action might influence good test results. The more user "get the hang of it" in imagining the motoric action, the more consistent EEG data pattern will be. This statement is supported by Wolpaw's study in 2002 which stated that successful BCI implementation is not only depending on flawless application design but also influenced by user's skill in reproducing the same imagination while using BCI [2]. Failure events in few of the scenario 1 testing session is mainly because of distraction experienced by subject so that subject cannot concentrating on reproducing the same imagination.

Better performance acquired in test scenario 2. In this scenario, SVM classifier is able to classify online EEG acquisition in desired way. Much better success rate indicates that, in this scenario, subject can reproduce much more consistent imagination in moving the right foot.

In scenario 3 and 4, SVM classifier cannot classifies online EEG data into desired class, provable by low success rate. The reason is that because SVM classifier cannot identify the unique pattern in left hand movement. SVM classifier simply treats the supposed signal noise (additional movement, present in scenario 3 and 4) as normal signal. So, without dedicated training of the specific action, in this case, action described in scenario 3 and scenario 4, SVM classifier cannot classify it in desirable way.

In test scenario 5, SVM classifier is able to classify online EEG data into desirable main activity, that is scenario 2. It can be seen in 4^{th} until 6^{th} session, the test result shows 100% success rate. But, in 7^{th} session until last session, the test result is inconsistent. This event might be influenced by subject's exhaustion because of the scenario's high complexity. The exhaustion causes subject to lose concentration so subject cannot imagine the supposed activity in proper way. Whereas stated in previous paragraph that BCI needs subject's ability to reproduce consistent imagination to work properly [2].

In scenario 6, SVM classifier is able to classify online EEG data into desirable main activity, that is scenario 2. But, the inconsistent line graph from the test result indicates that the SVM classifier cannot identify the unique pattern from scenario 2. This event might be influenced by addition of head nodding movement imagination. The SVM classifier treats additional activity as a whole new signal rather than signal noise from trained activity. So, SVM classifier cannot classify online EEG data into desirable class accurately.

The higher success rate in right foot movement scenario might be influenced by the subject's handedness , which is right-handed. The correlation of right hand and right foot can be seen in most stroke patient which tend to disabled in one side of the body. This handedness factor is proved by Qing Gao in 2011 whose stated that brain asymmetry in handedness is surely affecting motor imagery performance [14]. Handedness is a preferable way for human to use one side of the hand either the right hand or the left hand naturally [15].

This research uses Left Hand Movement and Right Foot Movement as a main test objects because of how human walks naturally moving left hand and right foot at the same time. So, it should be easy to imagine by most people.

4.4 Additional Speculation

According to Y. Wang study in 2007, the optimal electrode placement for Motor Imagery BCI is on C3 and C4 spot [16]. However, Emotiv EPOC all-fit headset doesn't have its electrodes placed in any of that spot. To make things clear, please check Figure 5 which shows international electrode placement standard 10-20 system and Figure 6 which shows Emotiv EPOC's electrode placement.

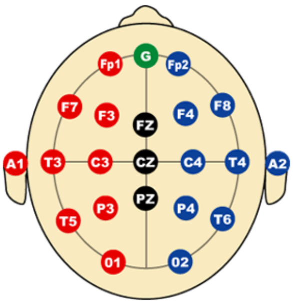

Figure 5 International Electrode Standard 10-20 System [17]

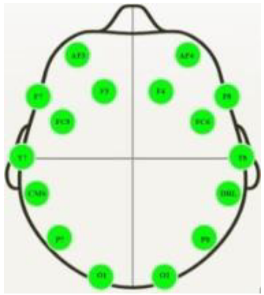

Figure 6 Emotiv EPOC Electrode Placement [18]

It can be seen that Emotiv EPOC doesn't have any electrodes placed on the supposed optimal spot for motor imagery BCI. However, Emotiv EPOC is still can be used for Motor Imagery BCI although not as optimal as the supposed spot. One of the factor that caused Emotiv EPOC cannot identify the desired activity when combined with other activity might be the electrode placement.

5. Conclusion

From the research that has been conducted, the success rates of those 6 scenarios are: 76,67%, 91,67%, 28,33%, 13,33%, 60%, and 76,67% for scenario 1 until 6 respectively. The conclusion is BCI can identify and distinguish intended activity by means of using intensively trained classifying algorithm with intended activity so that the classifier have reference data for the activity, then, the trained classifier is able to classify online EEG data into trained class according to the pattern. The reference EEG data must be processed first with time-based epoching to extract its feature vector per second and then correlated with the activity label so the classifier can associate data pattern with its respective label then use it as reference.

The usage of Emotiv EPOC as a data acquisition device and OpenVibe as the platform is the first time for Motor Imagery BCI. However, the usage of Emotiv EPOC as the acquisition device is not recommended because Emotiv EPOC cannot identify the unique pattern of trained activity when combined with another activity. It might be caused by Emotiv EPOC's electrode placement which is not optimal for Motor Imagery application.

Other than that, success rate of BCI usage is also heavily influenced by user's skill in reproducing the same imagination so that the EEG signal is consistent with the reference data.

6. Limitations and Future Research

In this study, it is concluded that EEG data pattern when human intends to do something can only be known by acquiring data for each user. But, this study cannot find any unique pattern which should be present in the activity. Other than that, Emotiv EPOC is just a consumer grade device, so the data acquired is not as good as the medical grade device, and the all-size all-fit concept from Emotiv EPOC is not as good as it sounds.

For future research in motor imagery, another device which have customizable electrode placement should be used. For accuracy testing, more subjects should be tested. Furthermore, application which can classify more than two activities should be developed to test the effectivity. Also add the neutral state of the application to ease the testing phase.

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