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Wireless Brain-Machine Interface Using EEG and EOG: Brain Wave Classification and Robot Control

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ABSTRACT

A brain-machine interface (BMI) links a user's brain activity directly to an external device. It enables a person to control devices using only thought. Hence, it has gained significant interest in the design of assistive devices and systems for people with disabilities. In addition, BMI has also been proposed to replace humans with robots in the performance of dangerous tasks like explosives handling/diffusing, hazardous materials handling, fire fighting etc. There are mainly two types of BMI based on the measurement method of brain activity; invasive and non-invasive. Invasive BMI can provide pristine signals but it is expensive and surgery may lead to undesirable side effects. Recent advances in non-invasive BMI have opened the possibility of generating robust control signals from noisy brain activity signals like EEG and EOG. A practical implementation of a non-invasive BMI such as robot control requires: acquisition of brain signals with a robust wearable unit, noise filtering and signal processing, identification and extraction of relevant brain wave features and finally, an algorithm to determine control signals based on the wave features. In this work, we developed a wireless brain-machine interface with a small platform and established a BMI that can be used to control the movement of a robot by using the extracted features of the EEG and EOG signals. The system records and classifies EEG as alpha, beta, delta, and theta waves. The classified brain waves are then used to define the level of attention. The acceleration and deceleration or stopping of the robot is controlled based on the attention level of the wearer. In addition, the left and right movements of eye ball control the direction of the robot.

Keywords: Brain-machine interface, Electroencephalography, Electrooculography, human-robot interaction

1. INTRODUCTION

A brain machine interface (BMI) is a communication system that translates human's thought into signals to control devices such as a computer application or a neuroprosthesis [1]. A BMI enables the brain to communicate with the external world by deciphering the brain activity. Hence, the assistive devices or systems using a BMI improve disabled people's quality of life. In addition, a BMI has been proposed to replace humans with robots in the performance of dangerous tasks like explosives handling/diffusing, hazardous materials handling, fire fighting etc. Earlier researches demonstrate the feasibility of BMI with the invasive method by implanting the intracranial electrodes in the motor cortex of monkeys [2]-[6]. While an invasive BMI can use good quality of brain signals, it is expensive and the implanting surgery may lead to undesirable side effects. A noninvasive BMI using electroencephalogram (EEG) signals are preferable for humans. EEG signals represent the electrical activity of millions of neurons in the brain. EEG has various properties and it can be used as a basis for a BMI: rhythmic brain activity, event-related potentials (EPRs), event-related desynchronization (ERD) and event-related synchronization (ERS) [7]. Different rhythmic brain activities are shown depending on the level of consciousness. The brain waves are classified according to the frequency band: Delta (0.1-3 Hz), Theta (4-7 Hz), Alpha (8-12 Hz), Beta (12-30Hz) and Gamma (30-100Hz). These rhythms are affected by different actions and thoughts, for example the thinking of movement attenuates or changes a typical brain rhythm. The fact that the thoughts affect the brain rhythms connote the rhythmic brain activities can be used for the BCI. ERP represents the potential changes in EEG that occur in response to a particular event or a stimulus. ERD and ERS is the change of signal's power occurring in a given band, relative to a reference interval. Many researchers have been developing a BMI with two different approaches. The first is a pattern recognition approach which is based on cognitive mental tasks and

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the other is an operant conditioning approach based on the self-regulation of the EEG response [8]. Pattern recognition approach detects different EEG patterns with different mental tasks. Because each different mental task activates its special EEG rhythm in different cortical areas, electrodes should be placed on the proper position to pick up the special EEG patterns. For example, the imaginary of the right hand movement activate the left motor cortex and the imagination of the left hand movement the right motor cortex. Meanwhile, the arithmetic tasks activate the prefrontal cortex. The operant conditioning approach is based on the self-regulation of one of EEG rhythms or event-related potentials. This approach differs from the pattern recognition approach. The users are not aware of any rhythms or event-related potentials happening in their brains unless they receive some kind of feedback. In general, a implementation of a BMI based on EEG signals requires measurement of EEG, preprocessing, feature extraction, classification and device control. To measure EEG signals, electrodes are placed on right places, typically according to the international 10-20 system. The preprocessing process includes amplification, filtration and A/D conversion. In the feature extraction stage, certain features are extracted from the preprocessed and digitized EEG signals in frequency or time domain. The extracted features are the input of the classifier. The classifier can calculate the probabilities for the input belonging to each class or the signals are simply classified by threshold detection. The output of the classifier is the input for the device control. The device control transforms the classification to a particular action of the device. While a number of research groups have been focusing on developing complex and multiple channels of BMI, in point of popularization and convenience of a BMI system, the BMI should be inexpensive and easy to use. In addition, the BMI should guarantee mobility.

The aim of this research is to develop a small wearable brain-machine interface to control a robot through wireless. In particular this research focused on how to implement a BMI which is cost-effective and has a small platform. The BMI controls the movement of robot by extracting the features of the EEG and EOG signals. The EEG and EOG signals are captured with gold nanowire electrodes attached on a headband [9]. The classified rhythmic brain waves are used to control the acceleration and deceleration or stopping of the robot by setting the threshold. The classified EOG signals from the left and right movements of eye ball control the change of left and right direction of the robot. Figure 1 shows the data flow of the wireless brain-machine interface to control the robot.

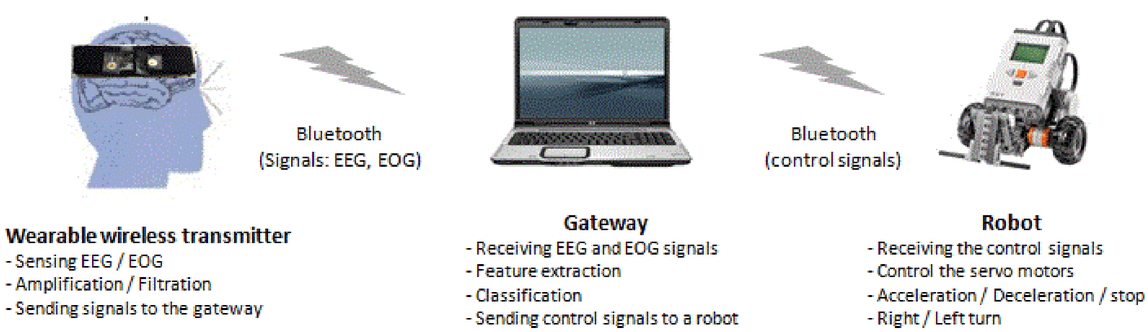

Figure 1. Data flow of the small wearable wireless brain-machine interface

2. SYSTEM DESIGN

2.1 System Architecture

A wearable wireless sensing transmitter mainly consists of two dry electrodes and a wireless transmitter module. Figure 2 shows the images of the headband and the wireless transmitter module. The electrodes are attached inside of a headband and the each electrode is electrically connected a snap button which is stitched outside of the headband. The wireless transmitter module is attached on the headband with the snap buttons.

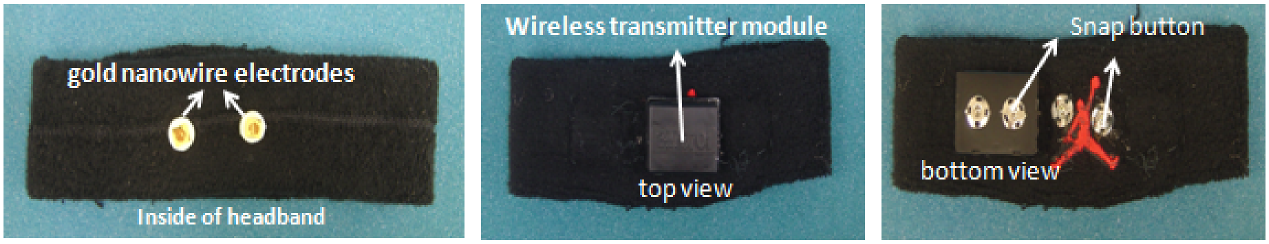

Figure 2. Image of the wearable wireless sensing transmitter

2.1.1 Sensor

Gold nanowire electrodes are used as the electrodes to sense the EEG signals [9]. The gold nanowire electrode does not need conductive gels which dry out and change the impedance of the electrode leading to erroneous or noisy EEG signals. In addition, the dry gold nanoelectrodes also have an unlimited shelf-life and reusable because of the inert nature of gold. Instead of placing electrodes on the hair site, the international 10-20 system, the electrodes are placed on the forehead. The good contact between scalp and electrode should be provided to achieve a good quality of EEG signals, but the connection through might be unstable causing noisy EEG signals. Forehead is a convenient location for placing electrodes and it is over the frontal cortex where cognitive signals linked to higher states of consciousness originate. In addition to detecting EEG signals, Because this BMI system also uses EOG signals, the electrodes should detect not only EEG but also EOG. Forehead is the suitable position to sense both EEG and EOG. Unlike the traditional EEG and EOG measurement system, the signals which are needed in the BMI are rhythmic brain waves and EOG from left/right eye motion. The other eye motions, up/down motion and blinking, are regarded as noises. These undesired EOG signals from eye motion can be rejected depending on the position of electrodes. The dry electrodes are spaced 5 cm apart and aligned horizontally. The horizontal alignment of electrodes enable to acquire higher amplitude EOG signals from left/right motion, but it does not provide the high amplitude EOG signals from up/down and blink motion because of reference electrode position.

2.1.2 Amplifier

EEG or EOG is a differential signal which is perceived as the difference in potential between two points, one of the electrodes acts as the reference for the other. The biopotentials has small amplitude ranging from micro-volts to a few milli-volts. Because the biopotentials are vulnerable to noises from power line (50/60 Hz) and mismatch between electrodes, high common mode rejection ratio (CMRR) and small input offset voltage should be considered when choosing and designing amplifier circuit. A multistage amplifier with high CMRR on the first stage, instrumentation amplifier, with two more stages of non inverting amplifiers are used to further increase the gain and improve the signals quality. The instrumentation amplifier provides the high input impedance as the first stage of the amplifier circuit and it prevents the distortion of EEG or EOG signals from skin contact impedance mismatch. The non inverting amplifier stages are designed with active filters. The filters help to prevent any aliasing artifact that can be produced during the analog to digital conversion. The overall frequency band of the amplifier circuit is set to 0.3Hz to 35Hz to cover the frequency band of EEG and EOG signals.

2.1.3 Microprocessor

The microprocessor plays role in digitizing the analog signals from the amplifier and controls the Bluetooth module. The microprocessor comes with analog to digital conversion (ADC) and timer resisters. Timer registers are counters which generate a signals, referred as an interrupt. The upper limit of the timer register can be set when the microprocessor is initialized based on the frequency of the count. Therefore, the interval can be fixed at which the interrupts are generated. This interrupt can be used as a trigger signal for ADC operation. Since the interrupt is generated periodically, the signal can be sampled with the same fixed interval. The ADC values are transferred serially to the Bluetooth module. The communication interface between microprocessor and Bluetooth module is Universal Asynchronous Receive/ Transmit (UART).

2.1.4 Bluetooth

Connection between Bluetooth devices can be established by profiles. The profile for a particular connection is chosen based on what kind of data needs to be sent form one device to another. In this system, The Serial Port Profile (SPP) is chosen because the data is a series of digits and SPP supports the continuous of transmission of data. We used a class 2 Bluetooth module, which broadcasts the SPP service and any Bluetooth device, like a phone or a Bluetooth enabled PC that comes within range can connect to this device on that profile and start receiving the data if the correct passkey is entered. The passkey is the first line of security for the data sent by the sensors. The data baud rate was set at 115.2 kbps which is a standard rate recognized by all microprocessor/microcontroller based devices. However, the data transmitted is not received by the data logging device, the data is not retransmitted automatically. The additional retransmit feature has to be implemented in software to improve the reliability of an SPP connection. Alternatively, the introduction of a special profile for health devices called the Health Devices Profile (HDP), by the Bluetooth Special Interest Group (SIG) is expected to be more robust and suitable for this application than SPP. Figure 3 shows the system block diagram of the wireless sensing transmitter.

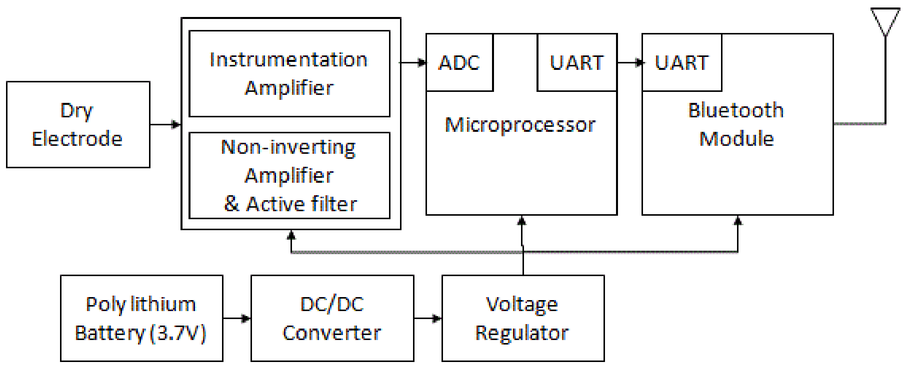

Figure 3. The block diagram of the wireless sensing transmitter

2.2 Feature extraction and Classification

EOG measures the resting potential of the retina according to the eye movement. In general, pairs of electrodes are placed either above and below the eye or to the left and right of the eye. If the eye is moved from the center position towards on electrode, this electrode sees the positive side of the retina and the opposite electrode sees the negative side of the retina. With this measurement method, all kinds of the eye movements are measured, left/right, up/down and blinking movement. In this BMI system, because only the left/right eye motion is supposed to use to make decision of left and right turning of a robot, the other up/down and blinking motions are considered as noise. Figure 4 shows the measured EOG signals with our headband system according to different eye motion. As shown in the Figure 4, the feature of blinking is narrow and sharp amplitude of waveform. The corresponding waveform of left and right motion is longer duration and somewhat dull peak of waveform. In common, the waveform of up and down motion is similar to that of left/right motion, but the signals from up/down motion is not detected much with this system because of the position of electrodes.

Figure 4. Measured EOG signals with different motions

Thresholds of amplitude and time duration are used to remove the blinking and up/down motion. After removing the undesired eye motion signals, only the left and right waveforms are remained. The two waveforms should be classified as left and right motion to send turning command to a robot. The classification between two eye motions is done by investigating the polarity of waveforms. Left and right motions shows the different polarity. In this system, left motion shows positive polarity and right motion, negative polarity, respectively. Figure 5 shows the classification processes of left/right eye motion. The left and right motion signals are filtered with 5~15 Hz bandwidth to achieve sharp waveforms to process further. After filtered, the floor noises are removed by setting adaptive amplitude threshold. The amplitude threshold is defined by the 75% of peak values of waveform. The cleaned waveforms by removing noise floor are used to decide the command signals. As shown in Figure 5 (c), now we have positive peak impulse and negative peak impulse. The positive peak impulse is mapped to amplitude 1 pulse and the negative peak impulse is mapped to amplitude 5 pulse. As shown in Figure (c) and (d), finally, left motion is processed the pulse amplitude 1 and followed by amplitude 5 pulse and right motion is the amplitude 5pulse and followed by amplitude 1 pulse.

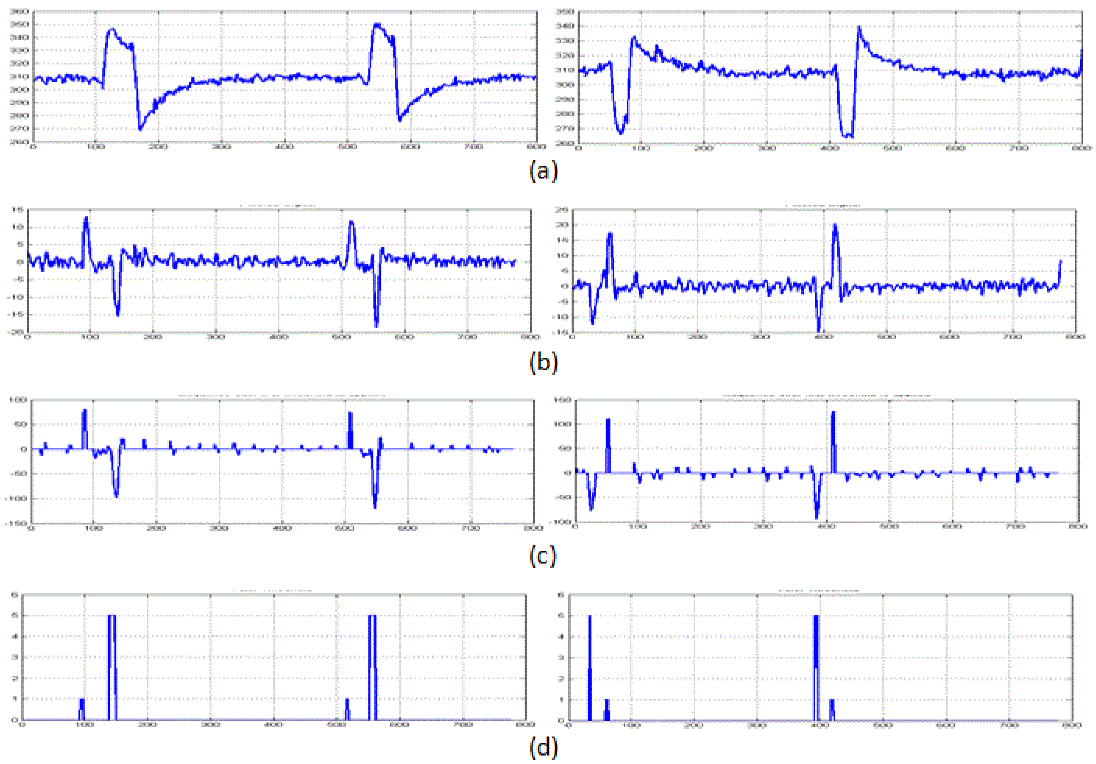

Figure 5. The Classification process of EOG signals; (a) raw left and right EOG signals, (b) filtered signals, (c) noise removed signals, (d) classified signals

Turning right and left of a robot is controlled by EOG signals, the acceleration and deceleration of a robot is controlled by EEG signals. Among several brain waves, we are focused on the alpha and beta wave because they represent the metal states of attention and relaxation respectively. The received EEG signals are transformed into frequency domain through Fast Fourier Transform (FFT) to investigate the brain waves. The each rhythmic brain wave are defined by the frequency band, and we can deduce the metal states by considering the amplitude change of frequency band. To simplify the EEG signals and extract their frequency components, the transformed signals by FFT are further processed by an autoregressive (AR) feature extraction method. To define the attention and relaxation level, the threshold are set based on the ratio between the sum of AR power spectral density (PSD) of alpha and beta waves. Figure 6 shows the change of AR PSD when eye opened and eye closed to check if the system can detect the alpha wave and beta waves. In addition, Figure 6 shows the bar graph to represent the sum of AR PSD value over each frequency band. Based on the sum of AR PSD value of alpha and beta frequency band, the ratio of alpha to beta is extracted and it is used to define the threshold of attention and relaxation. However, in case that floor noises cannot be ignored, the floor noise distorts the decision of attention and relaxation mode because the sum of AR PSD over frequency band includes all the noise and signals occupied in the frequency band. Instead of taking the sum of AR PSD value, taking the peak AR PSD value over the frequency band is more tolerant of noisy condition. Figure 7 shows the flow chart for feature extraction and classification to decide the attention and relaxation level.

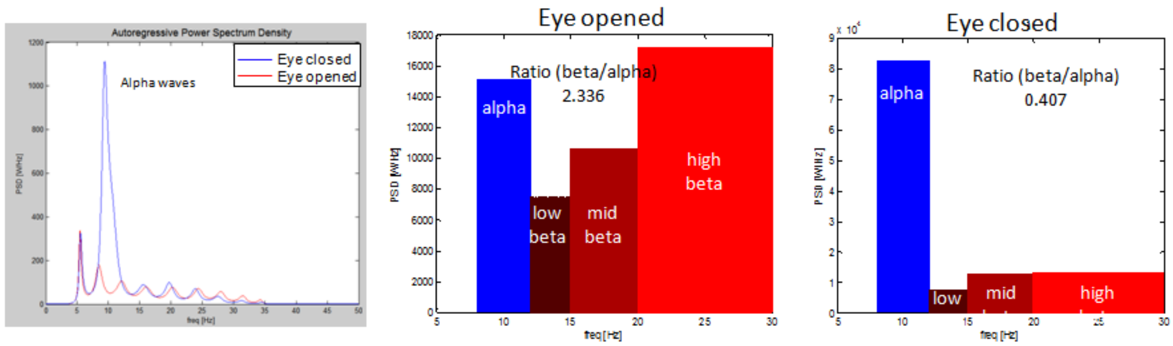

Figure 6. Plot of AR PSD of EEG signals

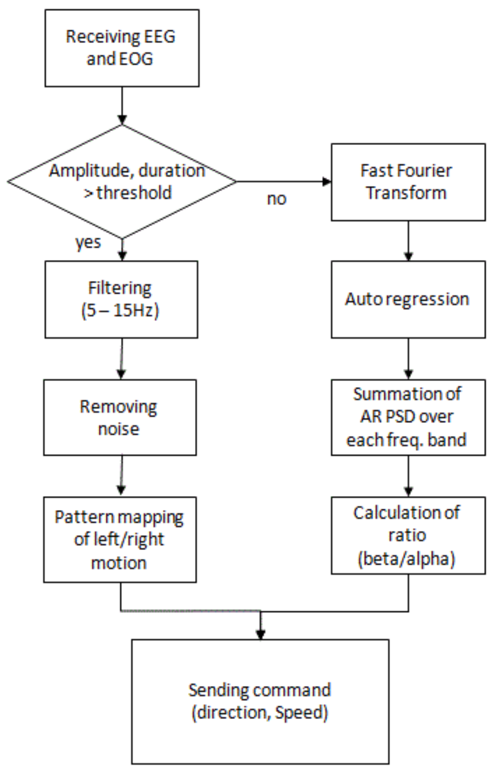

Figure 7. Flow chart for feature extraction and classification

2.3 Experimental Test

In order to validate the feasibility of the BMI system, Two experiment were designed. The first experiment is to control a remoter controlling a robot with this wireless BMI system. The controlling of a robot was performed by following the direction sign on the floor. The direction sign was designed with meander line style. The speed of a robot is controlled by attention and relaxation level extracted from EEG signals in the straight section and the changing direction of a robot is controlled by the left and right of eye motions in the curved section. In the second experiment, the subject was asked to make attention or relaxation by a experimenter and the calculated attention level was compared with the actual mental states of a subject. By performing the second experiment, we evaluated the accuracy rate of the BMI system.

3. RESULTS

We have characterized the data two different ways. one is using the sum of the PSD value over frequency bands to determine the attention level and the other is using the peak value of the AR PSD value over frequency band. Figure 8 shows the results of the sum of the PSD value with different references. The power over beta frequency band is divided by total power (alpha, beta, theta and gamma) and the beta power is divided by the power of alpha and theta which are related to the relaxation and meditation, finally the beta power is divided by the power of alpha. As shown in the Figure, the calculated the attention level from the power over frequency band does not show the consistence based on the instructed attention and meditation mode, i.e. in some case, even in spite of the subject stayed in the attention mode, the attention level has lower value than in the meditation mode. On the other hand, the peak value of PSD shows trends depending on the metal tasks. Especially, instead of using the all beta waves, beta waves are divided into low, mid and high beta waves. Even though beta waves are related to the attention state, subdivision can provide more accurate classification. Figure 9 shows the results of ratio the peak of the AR PSD value of low beta and alpha. In this experiment, the low beta which is related to the relaxed yet focused or integrated condition changes more than the other high or low beta wave. When we use the ratio of peak PSD value of low beta and alpha, the accuracy rate was about 92.6%.

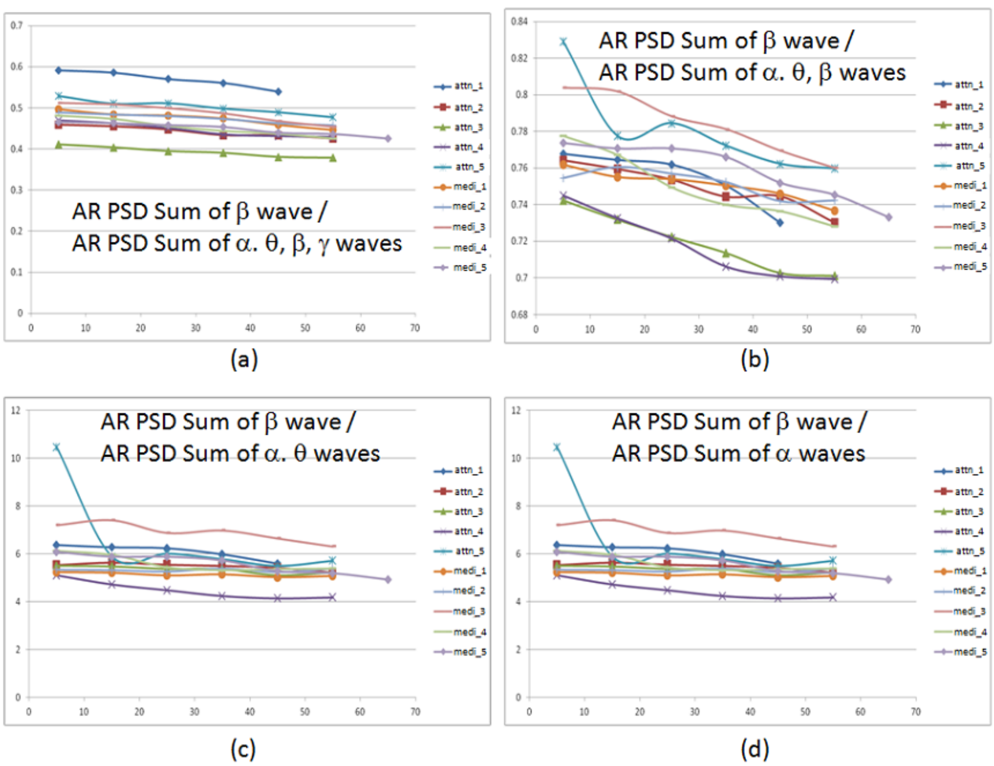

Figure 8. results of attention level based on different ratio: (a) ratio PSD sum of β to total power, (b) ratio PSD sum of β to PSD sum of α, θ, β waves, (c) ratio PSD sum of β to PSD sum of α, θ waves, (d) ratio PSD sum of β to PSD sum of α wave

4. CONCLUSION

The wearable wireless brain machine interface was developed to reveal the level of attention or relaxation and to control the robot. To verify the system, robot was controlled based on EEG and EOG signals and the classification algorithm to define the level of attention was evaluated with the experiment. The BMI system is a wearable headband type which has electrodes and wireless transmitter module. We used the gold nanowire electrode and bluetooth was chosen as the wireless communication method. The EEG and EOG signals are transmitted to the gateway (laptop). The EOG signals are extracted based on the amplitude and time duration. By using the threshold and polarity, the left and right eye motion can be classified and then the gateway sends command to make the robot turn right or left. The EEG signals are recorded and transformed into frequency domain. The peak value or sum of autoregressive PSD value of each brain waves is used to determine the level of attention. The level of attention is defined by the peak AR PSD value ratio of low beta and alpha waves. The results shows that the accuracy of the determining of the attention and relaxation is 92.6%. In addition, these feature extraction and classification algorithms were applied to control the robot.

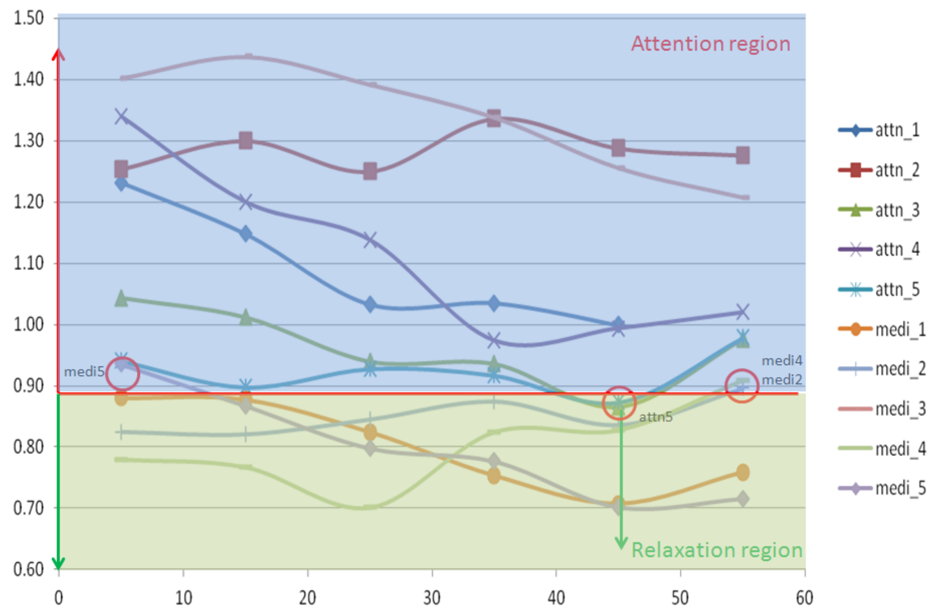

Figure 9. results of ratio the peak of the AR PSD value of low beta and alpha waves

5. ACKNOWLEDGMENT

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REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, " Brain-computer interfaces for communication and control," Clin. Neurophysiol., vol. 113, 767-791 (2002).

[2] J. K. Chapin, K. A. Moxon, R. S. Markowitz, and M. A. L. Nicolelis, " Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex," Nature Neurosci., vol. 2, 664–670 (1999).

[3] J. Wessberg, C. R. Stambaugh, J. D. Kralik, P. D. Beck, M. Laubach, J. K. Chapin, J. Kim, S. J. Biggs, M. A. Srinivassan, and M. A. L. Nicolelis, " Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," Nature, vol. 408, 361-365 (2000).

[4] M. D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. Donoghue, "Instant neural control of a movement signal," Nature, vol. 416, 141–142 (2002).

[5] D. M. Taylor, S. I.H. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," Science, vol. 296, 1829–1832 (2002).

[6] M. A. L. Nicolelis, "Brain-machine interfaces to restore motor function and probe neural circuits," Nature Rev. Neurosci., vol. 4, 417–422 (2003).

[7] Ali Bashashati, Mehrdad Fatourechi, Rabab K. Ward and Gary E. Birch, "A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals," J. Neural Eng., vol. 4, 32-57 (2007).

[8] Andrea Kubler, Boris Kotchoubey and Jochen Kaiser, "Brain-computer communication: Unlocking the locked in," Psychological Bulletin, vol. 127, 358-373 (2001).

[9] Vijay K. Varadan, Sechang Oh, Hyeokjun Kwon and Phillip Hankins, "Wireless Point-of-Care Diagnosis for Sleep Disorder With Dry Nanowire Electrode," J. Nanotechnol. Eng. Med., vol. 1, 0310121-03101211 (2010).