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Profound correlation of human and NAO-robot interaction through facial expression controlled by EEG sensor

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ABSTRACT

Emotion recognition from brain computer interface (EEG) has been studied extensively for the past few years. Time-frequency analysis is widely used in the past research; however, a variation of case study determines the brain signal analysis. In this paper, human emotion from brain waves is recognized in simple ways by calculating a frequency of signal variation. Entirely 35 healthy subjects from students with age 18-25 years old. The students are divided into 3 groups; the first group consists of 15 students; the second group consists of 10 students and the third group consists of 10 students. Each student takes 4 seconds to test his or her internal emotions. The signal speed is recorded during those 4 seconds. Based on stimulus time, various knocks for Z1 and Z2 is observed during a particular time. The experiment can be reproduced for in upcoming future by following the procedure. There are two main elements to measure signal speed which are ΔT and gap. ΔT subject to time differentiation of the changes in time-frequency of Alpha signals. For an evaluation of this work, there is an available benchmark database of EEG labeled with emotions; it mentions that emotional strength can be used as a factor to differentiate between human emotions. The results of this paper can be compared with previous researches which use the same device to differentiate between happy and sad emotions in terms of emotional strength. There is a strong correlation between emotional strength and frequency, we proved that sad feeling is speedier and beyond steady compared to happy since the number of ΔV to Z1 which represents sad emotion of Alpha signals is greater than ΔV to Z2 that represents a happy feeling in the same time period of the interaction process.

1. Introduction

EEG signal interaction with computer applications has become new natural interface in the current years. Many features extraction methods have been used in BCI researches. Some of these methods use the phase space of electroencephalogram (EEG) signals (Fang et al., 2015). Other studies are based on EEG coherence for feature extraction during the interaction process between the human brain and a computer. In addition to feature extraction (Salazar-Varas and Gutiérrez, 2015); various methods are used to classify different features based on EEG.

Electroencephalogram (EEG) has been used to measure the changes in brain activity which can be used in different fields. EEG signals are complex; therefore, fractal dimension has been used to describe the complexity of the EEG signals (Ibáñez-Molina and Iglesias-Parro, 2014). Some researchers used EEG to detect some diseases like epileptic seizure (Giorgi et al., 2014; Guo et al., 2010). EEG signals are analyzed based on age in order to show the difference in brain signals for each group of people (Knyazev et al., 2015). However, there are many important fields use EEG to explain, detect and

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solve different research problems and achieve different purposes.

EEG has been used to create an interaction between user and computer in many researches. Human emotion can be represented by different methods such as facial expressions, audio, visual and brain signals. Audio and visual methods are used together to recognize emotions in particular research (Sebe et al., 2006; Song et al., 2004). On the other hand, facial expression can be a strong tool to express human emotions which have been used in various studies (Ioannou et al., 2005; Kumar and Agarwal, 2014). This is done by using different techniques such as neuro fuzzy network and texture analysis of facial expression.

Detecting human emotion based on facial expression could be unrealistic. For example, humans can smile but it doesn't mean that they are feeling happy from their inner feeling. Therefore, this reason motivates many researchers looking for new methods to represent the internal emotions of people. For that reason, human emotions have been recognized based on measuring brain activity from EEG.

EEG can provide a more realistic representation of emotions because signals are more accurate than facial expressions. However, EEG has been used to achieve this purpose in many researches based on feature extraction. Time frequency analysis has been used to detect emotions from participants by using wavelet transform for feature extraction (Murugappan et al., 2008). Other researchers have recognized human emotions based on other features like higher order crossing (Petrantonakis and Hadjileontiadis, 2010). On the other hand, some related work focuses on emotion recognition based on correlation between left and right hemisphere of brain (Ahmed and Loo, 2014). However, there is different feature extraction methods used in this field. These features are used to represent the internal emotions of the human.

The previous algorithms focused on extracting different features to propose off-line emotion recognition methods. The main area of this paper to create an online emotion recognition method which can be used to represent the internal emotions of participants based on signal velocity. The purpose of this study is to calculate signal intensity by measuring frequency changes of brain signals during a specific period of time. We have calculated the average of collected data from participants to be represented as tables and graphs which will be explained in the results section. Time frequency domain is used as a method to calculate the frequency changes in a particular time. In addition, Alpha brain waves are the main parameters to extract signal speed because they are highly influenced by the emotion state of humans (Kubler and Muller, 2007).

Human Interaction with machine or robot has been studied extensively for the past decades. Lam et al. (2011) have proposed a framework for human-robot interaction, while Riduwan et al. (2013) and Yusoff et al. (2013) utilized Kinect depth camera to recognize human gesture for controlling medical visualization application.

2. Feature extraction

This paper presents a method to identify the speed changes of brain signals based on NIA EEG sensor that cover two basic emotions: happiness and sadness. NIA EEG sensor is capable on provide real time signal monitoring of Alpha and Beta signal from the brain. Therefore, hypothesis of this research is measuring the speed of the signal that monitored through EEG device and does classification to find certain emotion intensity of the human.

The input device is used to collect input data from participants and the features have been extracted from data inputs. After that, we separate the features into two different emotional groups in order to create real-time interaction between the participants and the facial expression of a virtual human. All these stages will be explained in detail in the experiment section

2.1. EEG sensor

There are numerous mind controller devices that used for gaming and bridging brain signal and its classification (Rosas-Cholula et al., 2010) and NeuroSky's mind headset (Crowley et al., 2010). Its commercial BCI devices that used commercially for entertainment and edutainment. NIA equipped with three sensors for reading brain signal of human brain that coming from frontal lobe as shown in Fig. 1.

On the other hand, there are several game applications used NIA for Human Computer Interaction (HCI) and game control by reading the brain signals from the EEG of the user (Zhang et al., 2010). NIA can be used for signal acquisition to obtain inputs in order to be classified in the next steps. It is one of the most effective devices which can be used in different applications of the BCI area by reading the EEG from frontal lobe of the brain. It reads Alpha and beta signals which represent the internal situation of the user and shows the signal during the process of interaction between user and computer.

Fig. 1: NIA EEG sensor

The human brain consists of four main parts, each with different functions. Brain waves are collected from the EEG based on the 10–20 electrode placement system that consists of 37 electrodes (Zhang et al., 2010). The focus study is reading signals from the cerebral cortex in the frontal lobe because it is associated with emotions and mental situations. Therefore, we are starting to calculate the velocity of signals from Fp1 and Fp2 channels which is located in the frontal lobe as shown in Fig. 2.

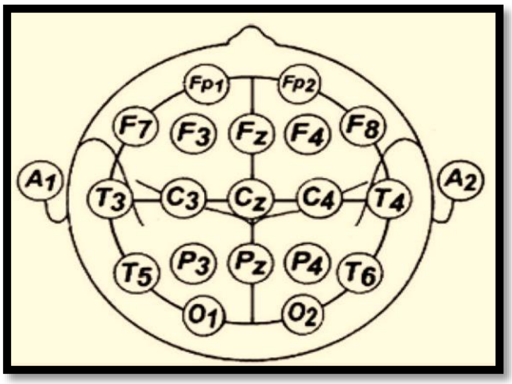


Fig. 2: 10-20 electrode placement system

2.2. Time frequency domain

The analysis of brain signals became very important and necessary in human life. The advantage of emotion representation can be applied in various areas for different applications. The EEG signals are divided into different bandwidths ranges with Alpha, beta, theta and gamma (Noachtar et al., 1999). Alpha (8-13 Hz) and beta (14-30 Hz) are used for emotion recognition because they have less undesired noise effect. This study focuses on the Alpha frequency band which is captured from the frontal lobe because it provides better results compared with beta in terms of calculating the velocity of the signals for happiness and sadness. The sensor device is used as a tool to read and explain brain signal activities as shown in Fig. 3. NIA activities consist of many parameters, Alpha1, 2, 3 and Beta1, 2, 3. These always change based on the real emotions of the user. The analysis process of these parameters during the interaction between user and computer will produce the required classification of brain signals based on the difference in the frequency changes for each emotion.

The aims of the study is calculating the speed of the Alpha signals that appear in Nia brain fingers frequency view in order to portray two basic emotions as a facial expression on a computer screen. The classification of brain wave signals is based on the emotional strength of each emotion. User brain activity is explained by the parameters of Alpha and beta signals as shown in Fig. 3.

These parameters represent EEG signals of user emotion which can be analyzed based on differences in the time for the changes in the frequency (Murugappan et al., 2008). The time-frequency technique is utilized to obtain the signal velocity for every feeling. This means that period, wave, and speed are required for the computation. The length of wave is measurable according to the curve shown in Fig. 4. Therefore, wavelength (λ) can be used to get the length of the wave.

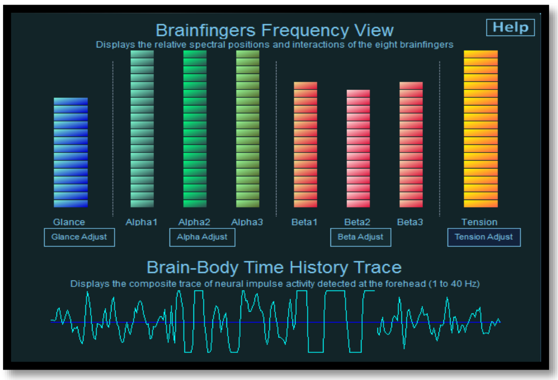


Fig. 3: NIA brain activities

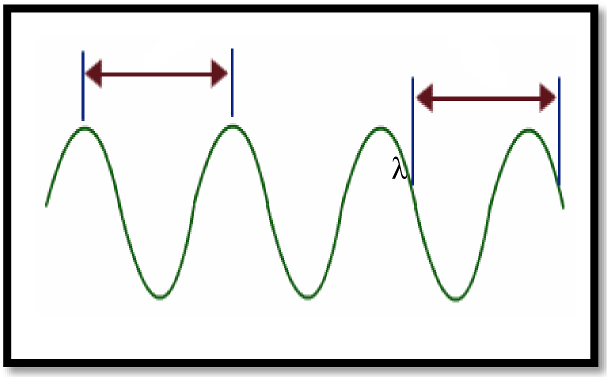


Fig. 4: Measuring the wavelength

Time is an important factor that should be calculated as a first step in order to get the velocity for each emotion. ΔT represents the difference in time between hits. ΔT will be calculated for a specific period of interval for every feeling, Eq. 1:

$$\Delta(T1) = \Delta(T1) - \Delta(T0)\} \quad (1)$$
$$\Delta(T2) = \Delta(T2) - \Delta(T0) \quad (2)$$

The first equation is to calculate the Δ(T), the values of Δ(T) based on the difference in the time to the change in frequency as shown in Eqs. 1 and 2. After calculating the values of Δ(T), velocity will be calculated as a second step by applying the Eq. 3:

$$Velocity\ \Delta(V) = \frac{\lambda}{\Delta(T)} \quad (3)$$

The wavelength of signal is characterized by a distance from initial point to end point. By using NIA, Each Alpha bandwidth wave is divided into five main zones which will be explained in the experiment section in more detail. These zones are used to clarify the change in frequency for each Alpha signal based through the signal occurrence for each zone and for each emotion. After applying the equations of delta time and delta velocity to the data inputs which are automatically stored in a text file, the final result will be stored as tables and represented as graphs in the next section.

3. Material and experimental method

In the beginning of the experiment part, the data inputs are extracted using an NIA based sensor device. During the interaction process between user and computer, the analyzing of the brain signals of students is the main focus in order to test their inner emotions. The process of experiment setup needs a basic requirement during the time of testing. These requirements are standard stimuli which are taken from the standard data set (Koelstra et al., 2012) to extract the required emotions from the participants.

The stimulus includes particular happy and sad videos for each emotion; therefore, the NIA input device is used as the main input at this stage. After completing the analysis process of the EEG data of participants, Facial Action Coding System (FACS) is used to represent the internal emotions of participants as avatar facial expressions in real time.

The Action Units (AUs) are created on facemask muscle motion to produce facemask languages on a virtual human. Facial expressions can be created by fusing certain AU to produce specific facial appearance (Basori et al., 2011; 2015; Basori, 2013). We have applied a method that consists of various steps. All steps are combined together in order to achieve the objectives of this paper. Fig. 5 shows the main infrastructure of this paper.

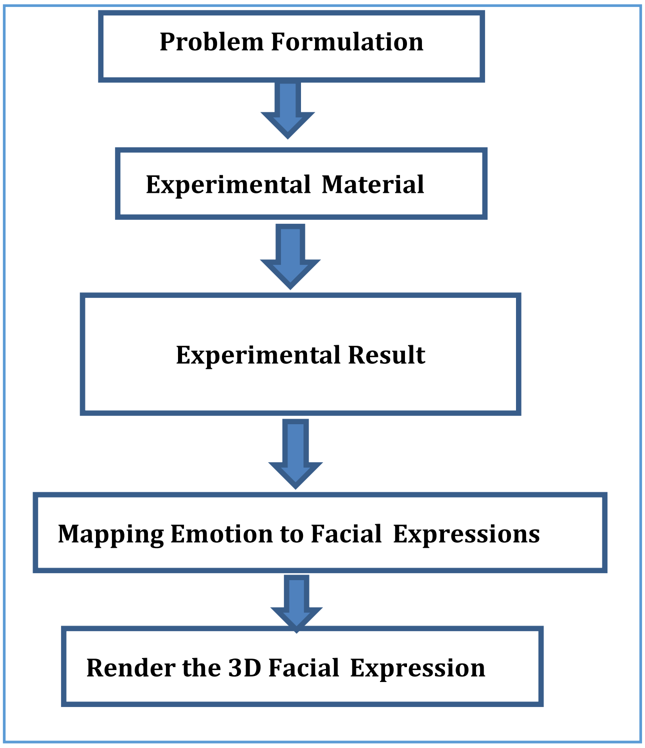


Fig. 5: Methodology

3.1. Problem formulation

The human brain consists of four main parts with different functions (Noachtar et al., 1999). This research is dedicated to study the frontal lobe of human brain which controls on human emotion functions. The representation of frequency bands on the screen is helping this work to get a good understanding of the internal emotion of the students. In this paper, feature extraction is related to the change in frequency of the signals.

The data input of this paper is collected from 35 male and female students aged between 18 to 25 years old. The students are divided into 3 groups; the first group consists of 15 students; second group consists of 10 students and third group consists of 10 students. After classifying the students into groups, we are preparing the environment for testing based on the next steps: The NIA device should be connected to the computer and the interface of the software device should be open as shown in Fig. 6.

Fig. 6: NIA device is connected to computer

3.2. Experimental material

The data gathering for experiment is based on laboratory setup that initiated by giving stimuli to participant by watching particular video. During the observation, students will be observed and their brain signal will be analyzed for certain period of time.

Five central regions that symbolize brain wave strength as shown in Fig. 7. Each student takes 4 seconds to test his or her internal emotions. The signal speed is recorded during those 4 seconds.

According to stimulation period, the number of knock for each zone (Z1, Z2) will be recorded and stored for further analysis. The experiment can be reproduced and adjusted according to the scenario. The main elements to measure signal speed are ΔT and gap. ΔT relies on the time variance of the changes in rate of Alpha signals which can be represented by the number of knocking (hit) for every zone. The distance for each zone is portrayed in Fig. 7.

During the recording process, the number of knocking in every region is displayed during different times. The quantity of knocking represents the variation in occurrence of the signal in milliseconds as shown in Table 1.

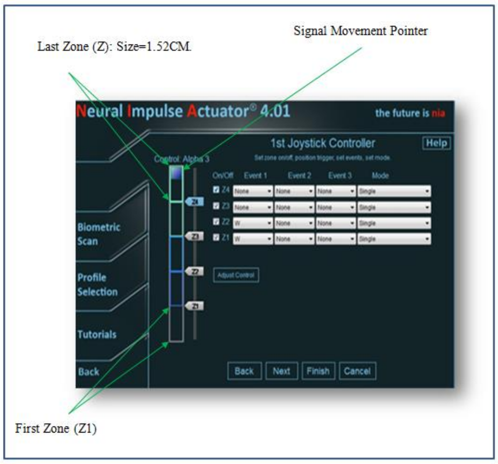


Fig. 7: Classification of alpha zones

Table 1: Sample of data for ΔT calculation

Number of knock	Hour	Minute	Second	Millisecond
1st Knock	10	37	05	720
2nd Knock	10	37	05	737

In Table 1, the first hit of Z1 was at 10:37:05 AM; and 720 milliseconds. The second hit of Z1 was at 10:37:05 AM; and 737 milliseconds. The value 720Ms is representing ΔT0 and the value 737Ms is representing ΔT1. Thus the calculation of Δ(T1) =737-720= 17Ms. The same rule is applied to erstwhile values. The computation of Δ(V) is founded by acquiring ΔT after former progression in addition to get the distance of signal movement.

3.3. Experiments results

The calculation of signal speed is based on two main factors which are time and distance. In this paper, the difference in time is relying knocking occurrence in every region during a particular period of time while distance is relying on the size of each zone. Z1 is linked with sad feeling while Z2 is linked with happy feeling due to their different strength (Tian et al., 2001). The area of signal movement consists of 5 zones in Fig. 7. The whole range of every region is 1.52 cm. The NIA device characterizes brain signal of Alpha in twenty blocks. Allocating 20/5, the outcome is four blocks for every region. In order to measure the distance, the size of every region (Z1, Z2) can be distributed into four extra regions in order to get the distance. As a result, 1.52cm/4= 0.38cm, this represents distance. The final result of the Alpha signals is calculated by using the Eq. 4:

$$\Delta V = \frac{0.38cm}{\Delta Tms} \quad (4)$$

The tables consist of ΔV computation of Alpha1 in Z1, Z2 and ΔV of Alpha3 in Z1 and Z2. Alpha signals are explaining the velocity of the signal during 4 seconds of testing. The result of signal speed starts from the ΔV1 to ΔV9 values which are measured in cm/millisecond. Tables 2 and 3 clarifies the changes in signal speed of Alpha1 and Alpha3 in the Z1 region that linked with sad emotion while Tables 4 and 5 clarifies the changes in wave velocity of Alpha1 and Alpha3 in the Z2 region that linked with happy feeling as portrayed in Tables 2-5.

Table 2: ΔV of Alpha1 and Alpha3 in Z1 zone (Sad) Cont'd

Z1	ΔV1	ΔV2	ΔV3	ΔV4	ΔV5	Cont'd
Alpha1	0.018	0.034	0.023	0.022	0.022	Cont'd
Alpha3	0.022	0.021	0.022	0.022	0.022	Cont'd

Table 3: ΔV of Alpha1 and Alpha3 in Z1 zone (Sad)

Z1	ΔV6	ΔV7	ΔV8	ΔV9	AvgΔV
Alpha1	0.022	0.021	0.02	0.027	0.023cm/ms
Alpha3	0.021	0.021	0.022	0.022	0.022cm/ms

Table 4: (ΔV) of Alpha1 and Alpha3 in Z2 zone (Happy) Cont'd

Z1	ΔV1	ΔV2	ΔV3	ΔV4	ΔV5	Cont'd
Alpha1	0.025	0.013	0.023	0.022	0.01	Cont'd
Alpha3	0.038	0.023	0.002	0.023	0.023	Cont'd

Table 5: (ΔV) of Alpha1 and Alpha3 in Z2 zone (Happy)

Z1	ΔV6	ΔV7	ΔV8	ΔV9	AvgΔV
Alpha1	0.023	0.023	0.022	0.022	0.023cm/ms
Alpha3	0.003	0.022	0.021	0.02	0.022cm/ms

Tables 2-5 show the signal speed during 4 seconds of experiments to 35 students. The changes in the velocity start from Δ(V1) to Δ(V9) which can be used to differentiate between Alpha1 and Alpha3 for each sad and happy emotion based on Z1 and Z2 zones. In addition, we calculate the average of the changes in signal speed (ΔV). From Tables 2 and 3, the average of ΔV to Alpha1 from ΔV1 to ΔV9 is 0.023 cm/ms and the average of ΔV to Alpha3 is 0.022 during the same time period.

In Tables 4 and 5, the average of ΔV for Alpha1 from ΔV1 to ΔV9 is 0.020 and the average of ΔV for Alpha3 is 0.019 for the same time period. We are recording the signal speed of the changes in frequency for students during showing them different happy and sad video stimuli. Z1 and Z2 are used to measure the changes in signal speed where Z1 is linked with sad feeling while Z2 is linked with happy feeling. The average values in Z1 (sad emotion) are more than the average values of the Z2 zone (happy emotion). As a result, the signal speed which is associated with sad emotion is faster and more stable than the signal speed of happy emotion. Figs. 8 and 9 are graphical representations of the ΔV values of Alpha1 and Alpha3 signals for happy and sad emotions are shown.

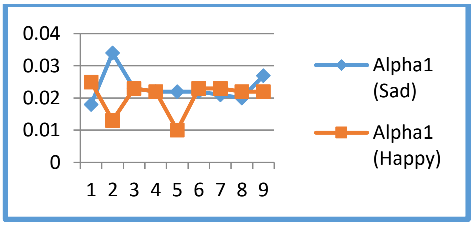


Fig. 8: The representation of alpha1 velocity for sad and happy emotion

In Fig. 8, we can see the difference between the blue and the red line which represents the difference of Alpha1 signal velocity between happy and sad emotions. The blue line is started from ΔV1 to ΔV9 and same is true for the red line. The blue line is represented the changes in the velocity for the data of sad emotion while the red line is represented the changes in the velocity for the data of happy emotion.

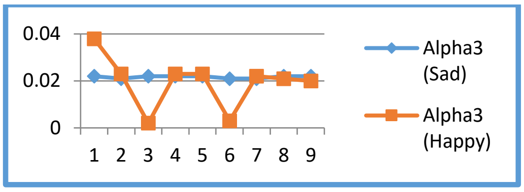


Fig. 9: The representation of alpha3 velocity for sad and happy emotion

As shown in Fig. 8, Alpha1 data for sad emotion are higher and more stable than Alpha1 data for happy emotion. On the other hand, Fig. 9 portrays the difference between the blue and red line which represents the difference in Alpha3 signal velocity between happy and sad emotions. The blue line is started from ΔV1 to ΔV9 and the same is true for the red line. The blue line is represented the changes in velocity to the data of sad emotion while the red line is represented the changes in velocity to the data of happy emotion. As shown in Fig. 9, Alpha3 data for sad emotion are higher and more stable than Alpha3 data for happy emotion.

4. Emotion classification

As mentioned in the previous sections, signal speed has been used to differentiate between two basic emotions. The experiments have been classified into two main sections. The first section is related to testing students and classifying two emotions based on signal speed while the second section is to create range of speed for each emotion in order to create a real-time system. The real-time EEG-based emotion recognition system can be used in different fields such as entertainment. For example, it can be used in human computer game interaction. At the same time, the real-time system can be applied in medicine fields; one of the main applications related to the medicine field is to help disabled people to improve their internal ability to express different emotions. In addition to the previous applications, there are so many other fields that can use this system to achieve various targets.

4.1. Facial action coding system

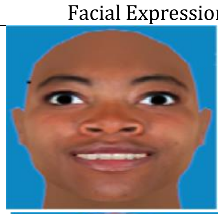
Facial Action Coding System (FACS) is a standard approach to measure facial behaviour to produce images. For example, facial muscle changes, and human anatomy. FACS divides each expression into units where each unit produces movement. Inner brow raiser, outer brow raiser, cheek riser are examples of facial units (Liu et al., 2010).

The facial expression is generated by combing the action units in order to get the required emotion. Facial expression researches have been ongoing for a long time. The human face has a number of expressions like happiness, sadness, anger, fear, surprise and disgust. This means that there are various methods which are used for facial expression control of a virtual human in a 3D environment. The researchers concentrated on these expressions being controlled by using different methods. Each of these action units referred to numerical code and possible solutions from models of emotional expression. The FACS system divides the face into three regions. Eyebrows and eye regions, nose region, and mouth region. The movement of AU for each region depends on each expression. The action units refer to the movement of facial parts of a single or a number of muscles (Basori et al., 2011).

4.2. Mapping emotion to facial expression

The analysis of human brain signals shows the influence of Alpha signals toward emotion classification to represent them as facial expressions through an EEG sensor device. The previous steps enabled us to calculate the velocity in order to obtain various speed for every emotion/feeling. Mapping emotion to facial expression includes converting brain signal into avatar facial expressions. The facial expressions of virtual human to each emotion are associated with the number of action units as shown in Table 6. The representation of human emotions as avatar facial expressions in this work is controlled by the frequency changing of brain wave signals. The signals are connected with the action units of the virtual human in order to represent happy and sad emotion as facial expressions on a computer screen. Each action unit clarifies a specific area of facial muscles, for example, AU23 (Lip-Tightened), AU1 (inner brow raiser), AU15 (Lip Corner) and AU4 (Brow raiser) are associated with muscles that generate a sad expression.

Table 6: Facial expression based on action units

Emotion	Facial Expression	Action Units
Happy		AU14, AU12, AU6, AU1
Sad		AU23, AU1, AU15, AU4

In addition, AU14 AU12, AU6 and AU1 are associated with muscles that generate a happy expression of the avatar. Brain signals which represent internal emotions that connected to avatar facial expression and Nao robots. The velocities of the signals for happy and sad emotion are connected directly to the action units of the avatar facial expressions. The system will read the three electrodes of the device on the frontal lobe of user's brain in order to capture signal and generate a real time online system as shown in Fig. 10.

4.3. Mapping emotion to robotic blink expression

Beside the facial expression, the authors also demonstrate the mapping of emotion expression from user to the NAO Robot. The happy emotion is expressed by bright LED, while sad with light reduced LED. Even though limited emotion that can be expressed through NAO, the experiment reveal promising result with an interesting NAO expression. Figs. 11 and 12 show the expression through NAO Robot.

Fig. 10: Real time emotion interaction

Fig. 11: Happy emotion By NAO eyes blink with blue/magenta colour

5. Result and discussion

BCI systems become an essential research area because they are associated with human-computer interaction. The primary aim of this paper is to classify two basic emotions happiness and sadness. The classification process is based on reading brain waves for each emotion as avatar facial expressions. This paper compares with a standard dataset (Ekman and Friesen, 1978) in terms of the influence of stimulus towards emotion classification. As a result of that, we are evaluating the result of this study by comparing with previous studies of emotion classification. For an evaluation of this work, there is available benchmark database of EEG labelled with emotions (Qian et al., 2012), It mention that emotional strength can be used as a factor to differentiate between human emotions (Tian et al., 2001).

Fig. 12: Sad emotion By NAO eyes blink with faded color

The analysis of emotions used particular stimuli to extract each emotion that relies on the velocity of Alpha signals to show the difference between two basic emotions. The reason behind using the previous stimuli is to prove that the stimuli which are used in this paper are suitable for obtaining the required emotions on the same environment.

The result of experiment shows there are different values in each table. In the implementation of Alpha1 signals, the velocity values of Alpha1 waves in Z1 are more than the velocity values of Alpha1 in Z2. Therefore, the Alpha1 data which are linked beside sad feeling in Tables 2 and 3 are faster than Alpha1 data which are linked with happy emotion in Tables 4 and 5. At the same time, in the implementation of alpha_3 signals, the velocity values of Alpha3 in Z1 are more than the velocity values of Alpha3 in Z2.

Hence, the Alpha3 data which are associated with sad emotion in Tables 2 and 3 is faster than the Alpha_3 data which are associated with happy emotion in Tables 4 and 5. The results of this paper can be compared with previous researches which use the same device to differentiate between happy and sad emotions in terms of emotional strength. The strong correlation between emotional strength and the change in frequency helps this work to have a better evaluation in terms of measuring the difference between happy and sad emotions based on the number of hits in the Z1 and Z2 zones. We proved that sad emotion is faster and more stable than happy emotion because the number of ΔV to Z1 which represents sad emotion of Alpha signals is more than ΔV to Z2 which represents happy emotion in the same time period of the interaction process. As a result, the analyzed data represent the internal emotion of the user and the natural interaction between user and avatar is generated. During this interaction, the facial expression of the user can be sad but the avatar expression is happy because this method is relying on real inner emotions not only facial expression. The second emotion expression through NAO Robot is quite interesting, even though the NAO eyes LED has limited color, the combination of strength and pretense color of NAO eyes LED can give different sensation to user.

6. Conclusion

The paper is focusing on finding a way to measure brain signal speed based on the changes in frequency during a specific time. Therefore, the main effort is to calculate the velocity of signal speed for each student. After that, we are calculating the average for all of them in order to be represented as tables and graphs as explained in the previous sections. Alpha brain waves are the main parameters to extract signal speed which is associated with the inner emotions of the user by using the time frequency domain as a method to calculate the changes in frequency in a particular time. Based on the reading of brain signal, it shows us a wide use a real-time system for analyzing human brain signals to cover two important emotions that can be used as a new product in different applications for example, a lie detector. Additionally, the proposed system can be used to help disabled people to represent their emotions and make contact with other people. In addition to the previous applications, the new product also can be used in police centers and acting institutes. The future work should focus on more than two expressions in order to show the difference between emotions in terms of signal speed and other additional features.

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