Entropy and Information Gain Analysis on Low Cost BCI for Motorbike Users to Prevent Accident

1st Rolly Maulana Awangga
Applied Bachelor Program of Informatics Engineering
Politeknik Pos Indonesia
Bandung, Indonesia
awangga@poltekpos.ac.id

2nd Syafrial Fachri Pane
Applied Bachelor Program of Informatics Engineering)
Politeknik Pos Indonesia
Bandung, Indonesia
syafrial.fachri@poltekpos.ac.id

3rd Dinda Majesty
Applied Bachelor Program of Informatics Engineering
Politeknik Pos Indonesia
Bandung, Indonesia
dindamesti@gmail.com

4rd Asep Setiawan
Applied Bachelor Program of Informatics Engineering
Politeknik Pos Indonesia
Bandung, Indonesia
asepsaktiawan18@gmail.com

5th Moch Yusuf Asyhari
Magister Program of Informatics Engineering
Universitas Islam Indonesia
Yogyakarta, Indonesia
17917213@students.uii.ac.id

***Abstract*—The phenomenon of mothers giving the wrong vehicle signal lights to turn left and right reminds the effect of giving the right signal lights to other road users. Weak human concentration while driving can cause errors when giving vehicle signal lights or not giving vehicle signal lights. Mistakes when giving a signal light a vehicle has a risk of an accident. The driver's brain wave data will show the results of the rider's brain thinking when turning. This study aims to analyze the concentration of the driver when driving. This research will obtain driver brain wave data when driving and analyze human brain waves while riding a motorcycle, especially when turning left and right, to reduce the risk of accidents while driving. The driver will use brain waves tool while driving, and the computer will detect the driver's brain waves, and then send brainwave data to the computer. Driver brain waves are analyzed using the formula entropy and gain. The results of the driver's brain waves become a decision whether the driver is allowed to drive on the highway based on the detected waves (alpha, beta, gamma, theta, and delta) to reduce the chance of an accident.**

***Index Terms*—Brain Computer Interface, Low Cost BCI, Turn Sign, Entropy, Information Gain.**

I. Introduction

EEG(Electroencephalogram) is a measure of brain activity, used in the fields of health and research, EEG functions to regulate the movement of the human body, the human brain has three parts, namely the cerebellum, cerebrum, and brain stem [1] [2]. In the brain, there are neurons and glial cells, these two cells communicate with each other, and glial cells are useful in protecting neurons [3]. Information on brain wave processes can be extracted and produce data sizes that depend on the human brain's resolution record. [4].

This time the EEG is used to check the rider's condition when turning right and left to analyze the possibility of an accident. The signal obtained will indicate the value of EEG data that needs to be analyzed. EEG signals consist of five types of frequencies, namely Alpha, Delta, Theta, Beta, and Gamma. The analysis will be done as a benchmark to determine the likelihood that data will enter the EEG signal in general [5] [6]. The available EEG sensor can receive messages that will implement for a long time. Therefore the EEG can provide information related to this activity [7].

The channel to communicate between the human brain and the computer or called BCI (Brain-Computer Interface) allows users to control the workings of the brain to the computer and translate the subject into application control commands [8] [9]. Communication that does not depend on the normal nerve output pathways peripheral and muscular, however automatic recognition is usually limited to a small number of class emotions mainly due to signal and noise features, EEG constraints and problems that depend on the subject [10]. EEG-based BCI can help the performance of brainwave readings that are tasked to produce EEG signals by imagining or when driving or certain motor activities, for example, will be applied to motorcyclists when turning [11] [12].

Driver Assessment base on EEG measurements to group waves or count waves obtained when turning right. It left, Specifically, provides EEG signals that describe the neural patterns in each brain displayed in the trajectory of steps related to modulation of each frequency, such as the depressing meaning [13] [14]. And will be used as a benchmark for the rate of neurosky brainwave delta 0.5 Hz to 2.75 Hz, Theta 3.5 Hz to 6.75 Hz, low Alpha 7.5 Hz to 9.25 Hz, Alpha 10 Hz to 11.75 Hz, Beta low 13 Hz to 16.75 Hz, High Beta 18 Hz to 29.75 Hz, Low Gamma 31 Hz to 39.75 Hz, Middle Class Gamma 41 Hz to 49.75 Hz [15]

II. Related Works

A. EEG

EEG is a non-invasive test that detects the activity of electrical waves in the brain using electrodes stored on an EEG device attached to the scalp where they place on brain

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cells communicating through electric current. Therefore, EE signals obtained from many channels [16] [17] [18]. EE signals are predictable physiological indicators and to measu the level of alertness. Generally explained, in this case, the frequency wave. EEG amplitudes obtained in the rang of 50-100 v, raw EEG signals are likely to be contaminate by unwanted non-brain origin signals called artifacts or sounc [19] [20]. Classification of EEG waveforms into five differe frequency bands namely alpha, beta, theta, delta, and gamm band [21] [22].

B. Brainwave

The brain has become the most difficult part of the body i the past. Still, with advances in brain science, skull activity ca be obtained using electrophysiological methods for brainwave communication. Take advantage of these changes for parts related to body parts and cerebral cortex areas [23]. Thoughts related to commands that lead to parts of the human brain, which are very dependent on the interpretation of the word brain and brain that have evolved in early [24]. The state of the brain can combine into two main models: the statistical and micro-activity model, the brain can be seen and considered as the reason for the hand given the order [25] [26].

C. Brain Computer Interface

Computer systems stop units from various levels. The brain's computer interface system uses brainwave sensors to obtain equivalent electrical signals from the brain produced by the activity of billions of neurons. Brain wave sensors consist of dry electrodes and reference electrodes. The raw data is then retrieved in the form of numbers and becomes a package number CSV [27]. BCI design for high amplitude and low-frequency EEG responses to external stimuli that recognize [28] time. Indeed, BCI research is popular nowadays. Because offline data analysis is free and can do on publicly available data, while offline studios can help guide BCI studios online, no offline security results are generalized to online support. When an algorithm extracts an EEG and translates it into a change in output, it changes the results that provide feedback to the user; thus, the user must change the next EEG signal from the user. The journal writing is to determine the brain waves and the concentration of the driver when turning left and right. The study uses an experimental method, calculation of entropy data, and gain on the driver's brain waves. In previous studies, not yet using the entropy calculation formula and gain in brain wave data. Research has not analyzed the brain waves of motorcycle riders, especially when turning left and right [29] [30].

III. Methods

A. Diagram of Research Methodology

Figure 1 shows research methodology diagram will explain the process of taking data and calculating the results into brainwave frequencies. Before the research process, the brain wave device or EEG was calibrated first because the equipment used was not consistent with the calculation of each test from the field. From the evaluation process will be discussed what kind of process part of this research methodology to calculate the frequency of brainwave results.

1) Tool calibration, Before the EEG tool, is used in the field, it is calibrated first because the tools used are inconsistent, the function for calibration here is to calculate one frequency data for a second.
2) Retrieve data from the field using an EEG tool with a motorcycle rider object by turning ten times right and left.
3) This rider use as an object for the process of data retrieval, a place to take in the field of the Indonesian post polytechnic campus with a track length of 25 meters.
4) calculation of frequency of brain wave, The data generated in the form of numbers with CSV file format and then used as a waveform from the results of these waves calculate and analyze to use as a criterion for these wave types.

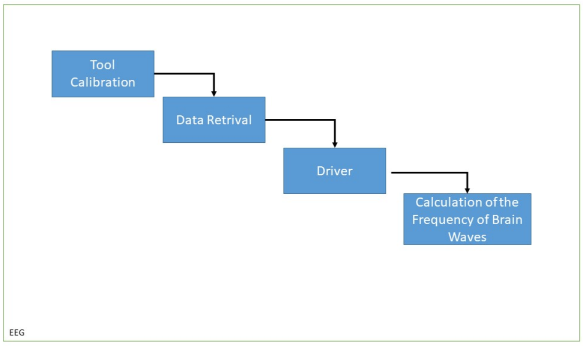

Fig. 1. Diagram Methodology

B. Calibration

These calibration results make into calculations with a lot of data that gets every 1 second, the results of the data will divide into one wave for calibration processes using python programming as an intermediary for data retrieval so that it can be a CSV format.

C. Data Retreval

This data collection process aims to make a working sample of the brain in humans when riding using a motorcycle with a length of 25m along with a 5m width limit on the work process at the Polytechnic field in Indonesia Post one test turn out as many as ten times the turn left and right.

D. Driver

The driver as a data retrieval object by using an EEG mounted on the head shows in figure 2. The sample image is an EEG or MindWave Headset tool. Data retrieval is carried out on the object ten times each turn. The computer is positioned in the middle to request a Bluetooth signal.

E. Calculation of Frequency of Brain wave

The process of collecting data in the field is useful for analyzing the driver's brainwave data when turning left and right. Brain waves consist of several categories, such as Delta waves that are detected when people are sleeping. Alpha waves appear when the eyes begin to close or when sleepy, while the beta wave is a condition when someone is doing daily activities or interactions with other people around. Gamma waves are detected when a person is at a very high level of activity.

Fig. 2. the process of installing a MindWave headset in the driver

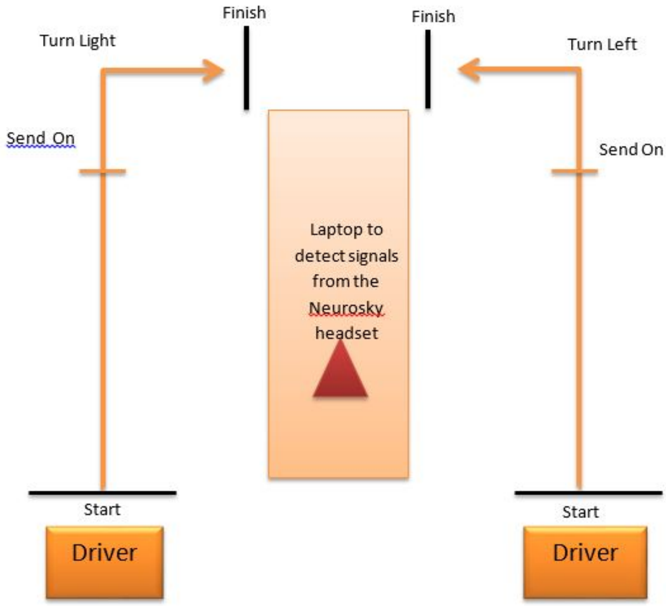

Fig. 3. layout of data collection process

Theta waves are detected when a person experiences emotional distress, such as sadness or disappointment. The type of wave results obtained will be calculated to find the entropy value and information acquisition value, as well as the formula for finding the entropy and information acquisition as follows. The following is the formula for calculating entropy:

$$Entropy(S)\sum_{n=1}^{n} -\rho i(log2)\rho i \tag{1}$$

1) S = case sets
2) n = Number of partitions
3) Pi = Proportion of SI to S

Then calculate the gain value using the formula:

$$Gain(S,A)\sum_{n=1}^{n} \frac{|si|}{s} * Entropy(Si) \tag{2}$$

1) S = Case set
2) A = The features
3) n = Number of attribute attributes A
4) Si = The proportion of Si to S
5) S = Number of cases in S

IV. EXPERIMENT

In the process of retrieving data, a test field creates with the aim that the driver does not make a mistake. Figure 3 explains the process of turning on and off the turn signal. When the driver has turned off the turn signal, the data will receive by a PC, which is 10 meters away. Brain waves function for retrieval of data on a laptop or PC in the middle so that the signals on the Brain Waves are not too far away. If the message on the Brain Waves is weak, the brain waves cannot find instructions when the driver stops to turn left or turn Good.

The result of object data

The test tool will appear, as shown in Figure 4. The object to do the experiment ten times turn left and ten times turn right, and the PC will receive the resulting data. The driver is needed without sweat to produce useful data because if sweat data is coming into the PC, the results are incompatible or cannot detect by this brainwave device or EEG. If the calibration of the data produced is not consistent, so it is most likely that the EEG equipment used cannot work correctly. The explanation is that sweat contains ions that make EEG unable to function correctly. EEG gel can overcome the problem of sweat on the driver because EEG gel can maintain the EEG conductivity properly.

1) Driver turn Right: Then the driver does the test by turning right like the Figure 4. This process is the same as when the process turns left with the number of trials ten times and turns on the lights to turn left and then turn off again. This process aims to get data when the concentration wants to turn left or turn right so that it can find out whether the resulting wave is a high concentration or regular. To find out the type of wave by calculating the length of the frequency produced by each object.

Fig. 4. The driver takes the data turn right

2) Driver turn left: The process of collecting data when the driver turns left in the field of Indonesian polytechnics on the object Figure 5 experimented ten times. Then the waves process the driver's brainwave data so that they can analyze several types of flow based on the results of the type of wave that has been analyzed, then look for the entropy value and get information.

Fig. 5. Turn recording data processing left

V. Results

In the I table shows data from seven objects which do the left and right turn tests. The most detected wave data is the beta wave, thus proving that the driver is in regular activity. In addition to beta waves, some gamma waves detect in the driver, and gamma waves indicate that the driver is in the highest concentration. Both of these conditions are the best conditions for the driver when driving. Data processing is performed using the entropy formula, and the gain entered in Excel. Comparison between wave data when the driver turns left and right shows that the driver has difficulty concentrating when turning right. This data indicates that the driver must be more careful when turning right. Entropy and gain calculations are useful for showing the results of brain waves detected in the driver. Wave data that serve as benchmarks for driver concentration are alpha, beta, gamma, delta, and theta.

TABLE I
Table Entropy and Gain

No			Case Total	Left	Right	Entropy	Gain
1	total		140	70	70	1	
	Object						2.220E-16
		Object1	20	10	10	1	
		Object2	20	10	10	1	
		Object3	20	10	10	1	
		Object4	20	10	10	1	
		Object5	20	10	10	1	
		Object6	20	10	10	1	
		Object7	20	10	10	1	
	Gelombang						0.035
		Delta	5	4	1	0.722	
		Theta	8	4	4	1	
		Alpha	6	2	4	0.918	
		Beta	111	52	59	0.997	
		Gamma	10	2	8	0.722	
	Amplitudo						0.077
		a1	6	3	3	1	
		a2	17	9	8	0.997	
		a3	107	48	59	0.992	

The first object is to experiment with riding a motorcycle. Then the driver turns left ten times while turning on the signal lights turn left. The experimental data shows that the rider is in good condition to drive because the brainwave detects beta waves in the driver. Beta waves indicate that the rider is in excellent condition: the next experiment, the object riding a motorcycle, and turning right while turning on the signal turn right. Brainwave detects weak beta waves on the rider. This experiment shows that motorists begin to lose focus while driving.

The second, third, and so on objects do the same experiment. The object turns left ten times and turns on the left turn signal light. This experiment produces data that is not much different from the previous object. Brainwave detects beta waves, which indicate that the driver is in good condition. Next, the driver turns left ten times and turns on the left turn signal light. Brainwave detects beta signals starting to weaken from before, because the object starts to feel tired, so the concentration begins to decrease. Therefore, drivers often forget or do not even turn on the turn signal lights. Detecting brain waves in the driver when turning left and right recommends resting first when tired when driving because mistakes in giving turn signal lights can cause accidents and endanger the lives of highway users

VI. Discussion

This research has limitations in terms of objects and equipment, so there are some shortcomings in obtaining data. If there is an error in getting data, then the calculation of entropy and gain and the results of the study will not affect decision making whether the driver is focused or not while driving. The detected waves will be different from the real condition of the driver. In this study, the more detected waves are beta waves, which indicate that the driver is in excellent condition while driving. When turning left, the driver is in excellent condition, but when turning right, the driver starts to get tired and lose focus, so the data obtained is not entirely right.

Suggestions for further research, when testing or taking data using EEG or Brain Waves, don't be in a hurry to do the test in the field. Be sure to get valid data without data errors caused by sweat or technical glitches from the driver, so that the resulting data is perfect and can control signals in brain waves. This study concludes that we can find out each type of wave that generates when turning left and turning right. This research is expected to reduce the accident rate by measuring or seeing the kind of waves in the driver's brain when turning right or left when the driver's concentration level starts to decrease.

This research has several factors that ignore, which are just complementary, hungry, and emotional. Some factors influence when retrieving data in the field if the driver sweats the resulting data is not optimal, the EEG signal to connect to a laptop cannot do at great distances, the batteries used to wear out quickly.

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