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Applying Decision Tree for Utility Control System on Patient Room using Eye Activity Command

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***Abstract*— Some quadriplegics are unable to move their limbs from hand to foot. They require an assistive gadget to help them to have a better life. An assistive device to control some apparatus in the patient's room was created using eye activity signals. This study aims to implement a decision tree for a utility control system in the patient room by using the eye activity command. Based on the user eye movement command, the decision tree is proposed to be implemented on the patient's room equipment control system. The eye movement electrode, data acquisition, noise removal, and signal pre-processing, and the decision model are involved to develop the system. In this study, four instructions are used, including the switch to the next option, switch to the previous option, activate an option, and start the systems command. These commands are represented by gaze to the left, gaze to the right, wink, and double wink. The holdout was utilized to validate the model by dividing data into 70 percent training and 30 percent testing sets. The decision model's accuracy is greater than 95%, according to the test results. This is an excellent outcome, and the model may be used in the system.**

Keywords*— *Decision tree, patient's room equipment, control system, eye blink, eye movement.

I. Introduction

Some people experience motor paralysis as a result of a condition like spinal cord injury [1] or amyotrophic lateral sclerosis (ALS) [2], which forces them to stay in bed. When someone has this problem, simple tasks like raising their arm, carrying goods, or traveling to other locations become impossible. To carry out these activities, these individuals require assistance from others. In other circumstances, the patient cannot undertake any tasks and merely lay on the bed. Because of the condition, these folks require some assistive equipment to aid them in completing their daily chores. An assistive device might be created that involve brain impulses or eye signals used as input to operate the peripheral for helping them with specific daily duties [3], [4].

Most of the time, ALS patients stayed in their rooms and lying on the bed. They may wish to adjust their bed backrest, turn on or off the light, and turn on or off the fan to make themselves more comfortable. However, using a remote or joystick remains challenging for individuals with motor paralysis [5]. Because most people with muscular and neurological system diseases can still move their eyes, Electrooculography (EOG) is a good option for those who need to operate some equipment [6]. The simplest biological signal derived from the human body is EOG. Eye activities, including eye blink and eye movement, may be used to control some equipment instead of using your hands. Many control applications, such as operating the house lighting system [7], wheelchair [8], [9], and hospital room equipment [4], [10], have relied on eye activities as input. Ocular movements [8] and eye blinks [4], [7] are examples of eye activities that can be utilized to operate the equipment.

In the research concerning device control utilizing eye movement, certain algorithms have been implemented. A threshold has been used to identify ocular activity [8]. The Fuzzy technique was used to detect if the eye blink appeared on purpose, with user attention level and blink strength as inputs [11]. The Artificial Neural Network (ANN) may also be used to identify eye movement when the signal is pre-processed to lower the dimensionality of the data [12]. The decision tree can also be implemented for eye activity detection [13].

The Classification and Regression Tree (CART) algorithm is a decision tree technique that is often used in research either for classification or regression problems. CART is developed by Breiman [14]. The CART algorithm has been utilized for a variety of applications, including to classify the blood donor [15] and drug absorption [16]. The decision tree algorithm can be utilized in the medical profession to identify disorders including stroke, hepatitis, and diabetic patients [17]–[19]. The decision tree has been implemented on detecting driver fatigue based on EEG signals [20].

According to the description given in the preceding paragraph, equipment control in the patient room can be implemented utilizing eye blinks and eye movements as input. This study aims to develop a decision tree that is used on a utility control system in an inpatient room based on the eye activity command. Moving the bed's backrest higher, moving the bed's backrest lower, turning the fan on/off, and turning the light on/off are all features that may be operated in the room. On the display of this system, numerous control choices are provided. The user can choose this option by blinking his

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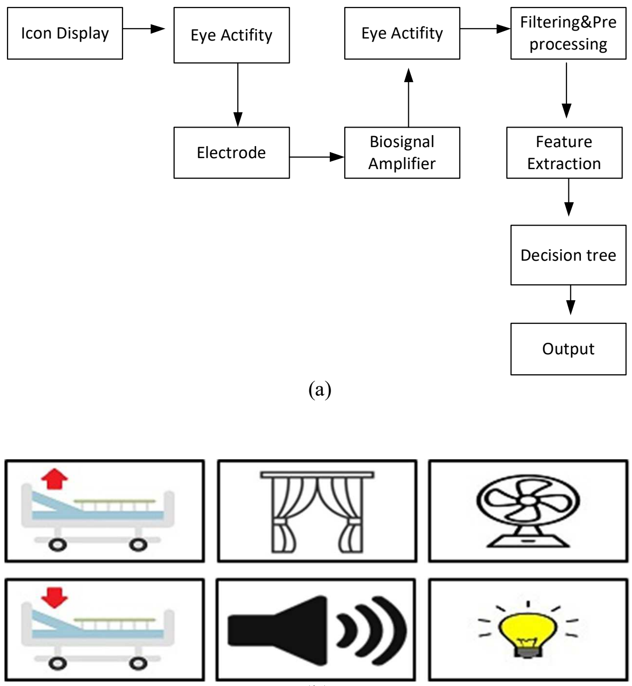

(b)

Fig 1. The Design of the System
(a). The System's Block Diagram
(b) The Desain of the Icon

or her eyes. The previous study only used one type of eye activity, such as blinking or moving the eyes. This research uses a combination of eye blinks and eye motions to increase the number of commands without using stimulation. In this work, feature extraction is also employed to minimize data dimensionality. The value of the positive and negative peaks, the time difference between the present location and the positive and negative peaks, and the time difference between two neighboring peaks are the characteristics recovered in this study. Because of the benefits of the decision tree, it is also employed in this study.

Introduction, approach, discussion of the result findings, and conclusion are the four sections of this work. The approach used in this work is described in Section 2, which includes gathering the data, pre-processing the signal, extracting the features, and developing the decision strategies. Section 3 summarizes the study's findings and discusses the establishment and application of the CART decision tree. This study's conclusion is drawn in the last part.

II. METHOD

A. Design of the System

This study offers a decision tree for leveraging eye blink and movement commands to operate electronics in a patient's room. The eye movement, including gaze left and right, is used to change the command menu while the eye blink is used to choose the command menu. The system is comprised of eye activity electrodes, collecting the data, filtering the signal, and extracting the signal features, and developing the decision strategies. In this study, the individual was requested to make certain eye movements, and the signal from those movements was recorded, pre-processed, extracted the features, and utilized as inputs to the decision algorithm. The design of the system is depicted in Fig 1.

There are several icons displayed on an Organic Light-Emitting Diode (OLED). The icons are used as a command for moving the bed up, moving the bed down, closing/opening the curtain, turning on a bell to call someone, activating/deactivating the fan, and turning on/off a lamp. Only one icon is displayed. The subject can switch between icon commands by a gaze to the left or right. While one icon is displayed, the subject can blink his/her eyes to choose the command that is represented by the icon. To start the overall system, a double blink command can be used.

B. Data Acquisition

During conducting this research, the participants were requested to sit while conducting the necessary eye activities. The participants were instructed to gaze to the left. This command is repeated twelve times with a 25-second interval between each action. The participants were then requested to gaze to the right twelve times with a 25-second interval for each command. Then the participants were required to blink twelve times for every order, with an interval of 25 seconds. And finally, the participants were asked to conduct double blinking twelve times and given 25 seconds for each command. The command of the wheelchair will be implemented based on each eye activity. The CART test class number is also provided for each eye motion. To control the device, each eye activity will be used as a command. For the constructing decision tree model, every eye motion is assigned a class number. Table I shows the class label, eye motion action, and its corresponding instruction.

The electrical signal from the subject's eye activity was captured and saved on a personal computer for subsequent processing when the subject performed this activity. To capture eye movement. the electrodes are placed on the left and right of the eyes, with the references on the forehead. With a sample period of 10 milliseconds, the signal that is read from the electrode is then amplified and recorded using Arduino. The data read by Arduino is then transmitted to the computer and saved for future study.

C. Signal Preprocessing

To guarantee that the collected signal is of excellent quality, many preprocessing procedures are included. Subtracting the ADC reading value from the initial reading, filtering the noise, and removing the baseline are among the data pre-processing procedures. The get the baseline removed signal, the captured ADC value was subtracted from is initial reading. The noise in the signal is suppressed using a second-order Butterworth low pass filter [21]. The discrete transfer function is then transformed from the transfer function of the Butterworth filter. The following equation is produced by deriving the difference equation from a discrete transfer function:

$$y[n] = 0{,}0055x[n] + 0{,}0111x[n-1] + 0{,}0055x[n-2] + 1{,}7786y[n-1] + 0{,}8008y[n-2] \quad (1)$$

where the x and y, respectively, indicate the signal input and filtered signal output. The indicators n, n-1, and n-m denote the sample points now, previously, and m-past. The filtered signal shows no flattening trend in the pattern. It is due to the quality of the equipment which is not very excellent, and the signal trend is increasing with time. The

trend of the signal should be modified such that the signal always has a flat baseline. To remove signal trends, the de-

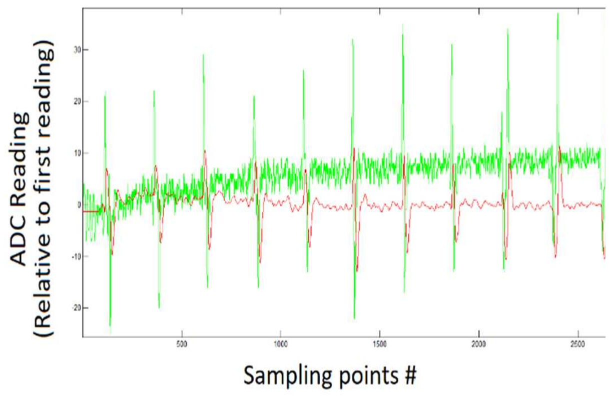

Fig 2. The Acquired and Pre-processed Signal

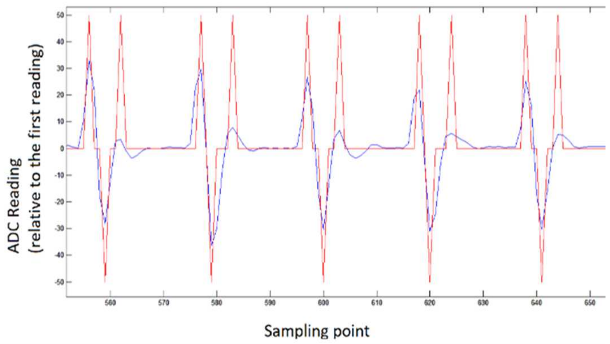

Fig 3. The Result of Positive and Negative Peak Detection

trend technique is needed. The trend is removed by eliminating the trend from the signal. For performing the trend emoval, a simple moving average technique [22] was deployed to get the signal trend.

The trend is determined with the mean of signal value which is calculated 100 points before. The pre-processed signal sample is illustrated in Fig 2.

The obtained signal is shown as a green line, whereas the signal after pre-processing steps is shown as a red line in Figure 2. After the de-trending process, the signal has a flattened trend as a product of pre-processing. Because the spike in the waveform is an essential aspect of the eye movement signals, it is kept. When compared to the green line signal, the red line signal has less noise.

D. Feature Extraction

Following the pre-processing procedures, feature extraction is the next stage. The signal is downsampled by ten times to ensure the calculation is easier. Identifying the negative and positive peaks is used to extract the features. If the magnitude of the signal is larger than the positive threshold, preceding, and succeeding value, it is considered a positive peak. If the magnitude of the signal is smaller than the negative threshold, preceding, and succeeding value, then the signal might be recognized as a negative peak. Figure 3 depicts the outcome of positive and negative peak detection.

The negative and positive peaks can be accurately recognized, as shown in Fig 3. The pre-processed signal is shown by the blue line, while the negative and positive peaks are represented by the red line. The values of the positive, prior positive, negative, and prior negative peaks are all

TABLE I. THE CLASS LABEL, EYE MOTION ACTION, AND ITS ASSOCIATED INSTRUCTION

Class Label	Eye Motion Action	Associated Instruction
0	Looking to the front	No activity
1	Gaze to the left	Switch to next command
2	Gaze to the right	Switch to previous command
3	Blinks	To choose a command
4	Double blink	Start the system

extracted from the detected peak. The signal is also used to derive the time difference of the present position to the negative and positive peaks. The time difference of the two neighboring negative and positive peaks was also extracted. The retrieved feature is then utilized in the following procedure.

E. Decision Model

Because they can provide clear results, decision tree algorithms have maintained their appeal. For splitting, ID3 utilizes information gain [23], whereas C4.5 uses gain ratio [24]. CART is an alternate decision tree construction method in this case. It can do both classification and regression tasks. To produce decision points for classification problems, this method employs a novel statistic known as the Gini impurity [18].

Gini impurity is a calculation on how frequently a randomly picked element of the data would be wrongly classified if it were randomly categorized based on the distribution of labels in the data. Gini Impurities is adopted by the CART method to create trees for classification purposes. The Gini impurity is calculated based on the probability p_i of an element with label i being picked by the probability $\sum_{k \neq i} 1 - p_i$ of incorrectly classified. Therefore, the Gini Impurity can be calculated as

$$I_G = 1 - \sum_{i=1}^{j} p_i \quad (2)$$

Where I_G is the Gini Impurity, and j is the number of target classes. When all cases in a node fall into a single goal category, the Gini impurity hits its minimum (zero).

Most decision tree algorithms are built in a top-down manner, with all training instances starting at the root node. The second step is to choose an attribute based on the splitting criteria (Gain Ratio or other impurity metrics). The next step is to recursively divide instances based on the specified characteristic. The partitioning will be stopped when:

- there are no more examples for a particular node.
- all examples for a specific node belong to the same class.
- there are no more characteristics for further splitting - the majority class is the leaf.

III. RESULT AND DISCUSSION

The research was carried out by using MATLAB to analyze the collected data and create the optimal decision tree model. The pre-processed and extracted features from the collected signal are then utilized to build the decision tree model. This study used the hold-out validation model. The validation model uses 70% of the data from the training set and 30% of the data from the testing set. In this investigation, 884 instances were employed, including 619 training

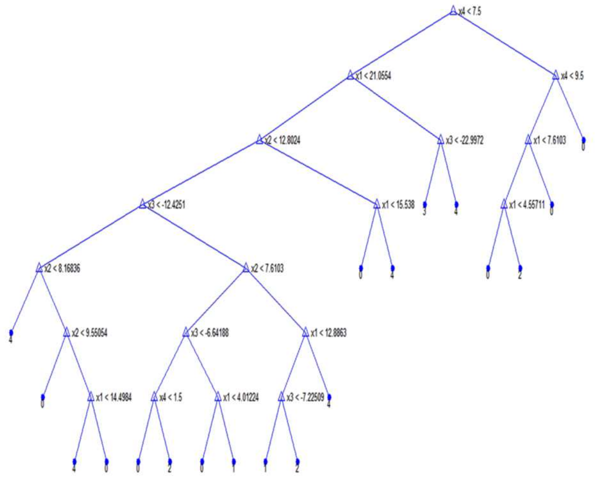

Fig 4. The Training Process of the Decision Tree

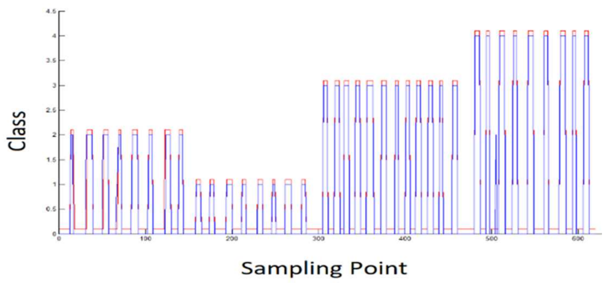

Fig 5. The Result of the Decision Tree Training Process

instances and 265 testing instances. The testing set is chosen at random from the data. The data that was not picked will be utilized as a training set. The information is subsequently utilized in the computer's calculation process.

A. *Decision Tree Model Development*

The feature that has been extracted is applied to the decision tree as an input. The feature that is used in this study is the value of the positive amplitude, preceding positive amplitude, the negative amplitude, and the preceding negative amplitude. The time-related features were also used as the decision tree inputs. The time-related features are the time difference between a current position and the positive amplitude, a current position and the negative amplitude, two adjacent positive amplitude, and two adjacent negative amplitude. Only a few of the features were chosen as inputs to the decision tree based on their connection to the target, to minimize the data's dimensionality. The magnitude of a positive amplitude, the magnitude of a preceding positive amplitude, the magnitude of a negative amplitude, and the time difference of a present location to a positive amplitude are the four characteristics that are utilized as attribute input. The decision has five outputs: no action (class 0), gazes left (class 1), gazes right (class 2), blinks (class 3), and double blink (class 4). The decision tree that has been developed is depicted in Fig 4. The result of the decision tree training process is depicted in Fig 5.

The outcome of the decision tree training procedure is shown in Fig 5. The target class is represented by the blue line in the image, while the red line depicts the decision tree's classification output. The data is organized into four classes:

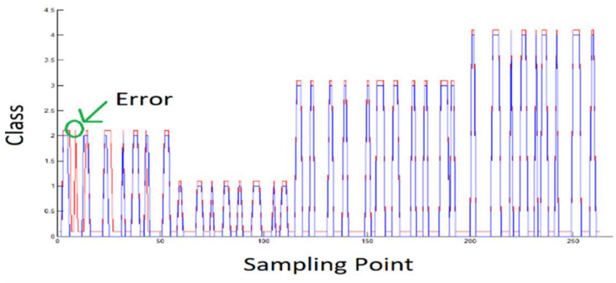

Fig 6. The Result of the Decision Tree Testing Process

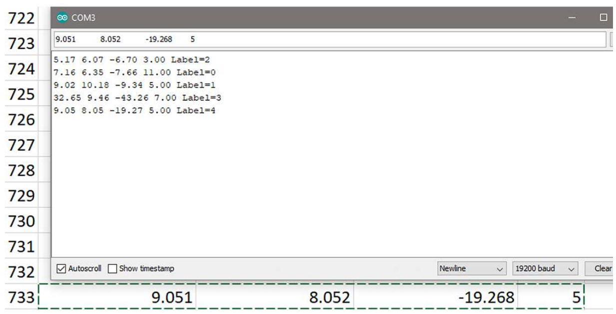

Fig 7. The Result of the Decision Tree Implementation

gazes right, gazes left, blinks, and double blink, which are represented by the numbers 2, 1, 3, and 4. There is repetitive eye movement that has been done in each lesson. In between the activity, there is no action. A zero value represents no action. The picture depicts how a decision tree may produce almost the same results as the target class. There are still some mistakes in the decision tree, such as the section highlighted by the blue circle in the picture. The decision tree training procedure has an accuracy of 99.9% and 98.87%, by ignoring and obeying the no action command, respectively. This is an excellent outcome.

The constructed decision tree model is then put to the test with the testing data. The decision tree's testing result is given in Figure 6.

The outcome of the decision tree testing method is shown in Fig 6. The goal class is represented by the blue line in the picture, while the output of the decision tree classification is shown by the red line. The decision tree still produces some errors, as seen by the red circle in the diagram. The decision tree testing procedure has an accuracy of 93.47% and 97.72%, by ignoring and obeying the no action command, respectively. This is an excellent outcome [25].

The suggested technique had a lower mistake rate than the work on operating a wheelchair by using EMG [5], which had a 4 percent error rate. Another experiment was carried out to operate the wheelchair by using eye activity [9]. This study's error rate is higher than the recommended approach's error rate. The decision tree has a lower mistake rate than the Fuzzy technique of eye activity detection [10], which has a 9.41 percent error rate. As a result, the proposed technique produces a superior outcome and is appropriate for use to control the equipment in the patient room.

B. *Decision Tree Implementation on the Hardware*

The hardware is then used to implement the decision tree model which has been created and validated. The hardware implementation is conducted by using Arduino. Fig 7 depicts the output of the decision tree implementation.

The output of the decision tree implementation procedure is shown in Fig 7. Various data is supplied to Arduino over a serial connection in the decision tree testing on the hardware. The serial communication was used to send 4 feature data. These values were returned to the PC over a serial connection and shown in the Arduino IDE serial monitor. The output of the decision tree was then computed by the Arduino and delivered to the PC through a serial connection. The outputs for classes 0, 1, 2, 3, and 4 are delivered to the PC as four separate outputs. The results are then compared to the decision tree output, which is generated by a computer. Fig 7 shows the serial monitor's output. Based on Fig 7, the decision tree realization test demonstrates that the Arduino can provide output that is identical to that of a computer-based decision tree. As a result, the decision tree implementation is functional.

IV. Conclusion

The decision tree is designed to be used in a patient's room appliance control system that is based on eye gaze instructions. The system comprises of an eye motion electrode, collecting the data, filtering the signal, and pre-processing signal, and extracting the signal features, as well as developing a decision model. There are four commands involved in this analysis. The instructions are left gazes, right gazes, blinks, and double blinks for the switch to the next option, switch to the previous option, activate an option, and start the systems command, respectively. The hold-out method is carried out by splitting the dataset into a 70% learning set for developing the model and a 30% testing set. The training results demonstrate that by ignoring and following the no-action instruction, the decision model's training method has an accuracy of 99.9% and 98.87 percent, respectively. The test results demonstrate that by ignoring and obeying the no-action instruction, the decision model has an accuracy of 93.47 percent and 97.72 percent, respectively. This is a favorable finding, and the model may be used to improve the system.

The research is carried out using computer simulations on MATLAB based on the collected data, as well as simulations on the hardware implementation. Before the system can be utilized, it must pass a test in a real-world setting. Some tests, such as reply time tests and user acceptance tests, must be carried out. Additional features, such as a communication and entertainment control system, can be appended to the system for enhancing the device's usage.

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