Discrete Wavelet and Neural Network Algorithm for Real-time Identification Finger Movement

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Abstract. Electromyography (EMG) Signals from human muscles can be utilized in various fields. One of them is in the control field. Some control systems use a person's finger movements. So, an algorithm is needed to recognize hand movement patterns. This paper examines systems' capabilities using neural network algorithms with discrete wavelet transforms. The signal is obtained from the EMG signal generated by the surface EMG sensor. This sensor is issued on the user's upper arm. This study used three healthy subjects with five-finger movements. This system is able to recognize patterns of finger movements, about 79.79%.

Keywords: EMG, Discrete Wavelet, Neural Network, identification.

1 Introduction

Robotics is a rapidly developing field with applications in many areas, including assisting with tasks that require precision or are performed in dangerous areas. These technologies can also be used for diagnosis, medication administration, and injury avoidance in the medical field.

Biomechanics, the study of human movement, also contributes to developing new technologies. One example is electromyography (EMG), which uses signals generated by muscle contraction to control devices such as hand robots [1] and prosthetic hands [2]. This technology is particularly beneficial for people with amputations.

Two standard methods for reading EMG signals are inserting sensors into the skin or detecting the signal on the skin's surface [3]. Most users prefer the latter method. The raw signal from EMG sensors must be processed using various techniques, including pattern recognition methods [4].

To recognize EMG signals, the characteristics of the signal must be understood. There are three types of domains for understanding the features of EMG signals: Frequency, time, and time-frequency [5]. Several algorithms have been studied for recognizing hand poses,

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including K-Nearest Neighbor (K-NN) [6], Linear Discriminant Analysis (LDA) [7], Neural Network (NN) [7], Fuzzy [8], and Artificial Neuro-Fuzzy Inference System (ANFIS) [9].

This study utilizes the frequency domain using discrete wavelet transformation. Discrete Wavelet Transform (DWT) is one of the tools for analyzing and processing signals and images, allowing for efficient representation of information at different scales and frequencies. It has found applications in various fields, including vision and audio processing, data compression, and feature extraction [10]. For the identification process, the Neural network algorithm is used. The study covers the data acquisition and signal characterization, the success rate of gesture recognition, and a summary of the findings.

2 Methods

This study used a Myo armband to detect EMG signals. The signals were processed on a PC with a Core i5 processor and 8GB RAM. Figure 1 shows the diagram blok of the system. The myo armband has eight EMG sensors. The armband is placed in the middle of the subject's right arm. The sensor number 4 was located approximately in the middle of the back of the hand (see Figure 2). The subject sat in a chair with their hand on a desk to obtain the signals. The subject then moved their fingers through eight gestures, as shown in Figure 3. The gestures are relaxing, close all the fingers, open all fingers, and open the thumb, index, middle, ring, and pinkie finger. Three healthy men have become subjects of this study. The average age of the subjects is 21 years old.

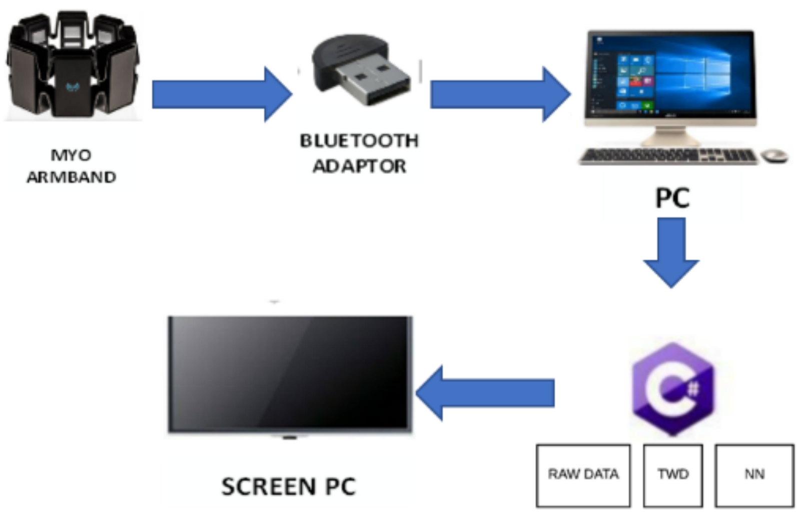


Fig. 1. Block diagram of the system

Fig. 2. The placement of the sensors

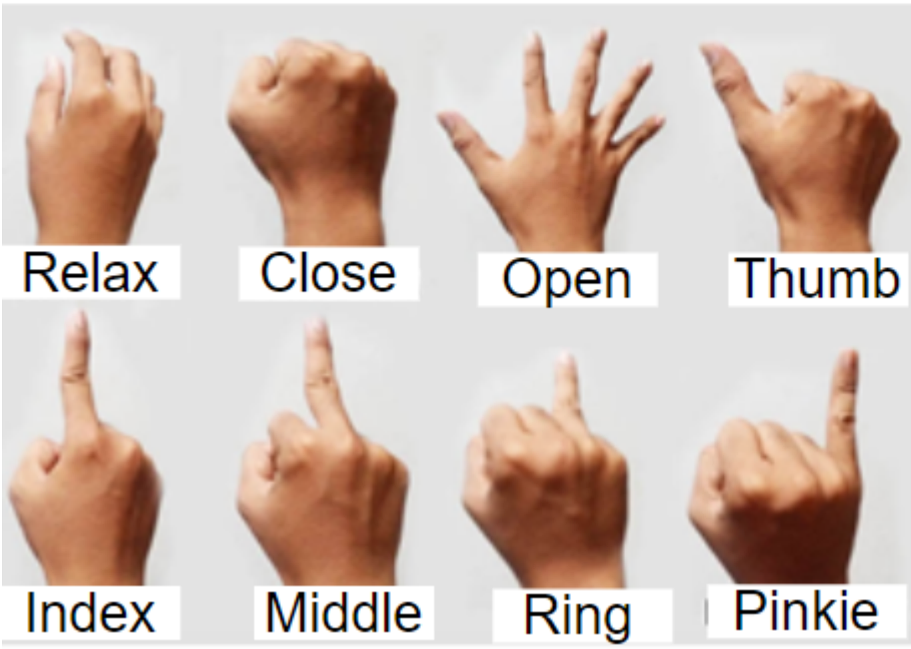


Fig. 3. Gestures of the fingers

The system used two phases to identify the movements of the fingers: a training phase and a test phase. The flowchart of both steps is shown in Figure 4. The EMG signals from the sensor on the subject were then converted to the frequency domain using DWT. The Discrete Wavelet Transform (DWT) is a mathematical technique used for signal processing, data compression, and image analysis. It divides a signal into different frequency components, making data representation more efficient. This is achieved by filtering the signal through low-pass and high-pass filters, creating multiple scales. At each level, DWT produces wavelet coefficients that represent features of the signal at that scale. Unlike continuous wavelet transforms, DWT deals with discretely sampled wavelets. Subjects are requested to activate their right hand. Each subject moves their hand appropriately with the eight gestures. They actuate each motion one hundred times.

Using the algorithm, the Neural network weights for recognition of the gestures. In the test phase, the neural network algorithm with the weights obtained from the training phase was used to identify the gesture the subject made. Each subject drives one hand a hundred times for each motion in real-time.

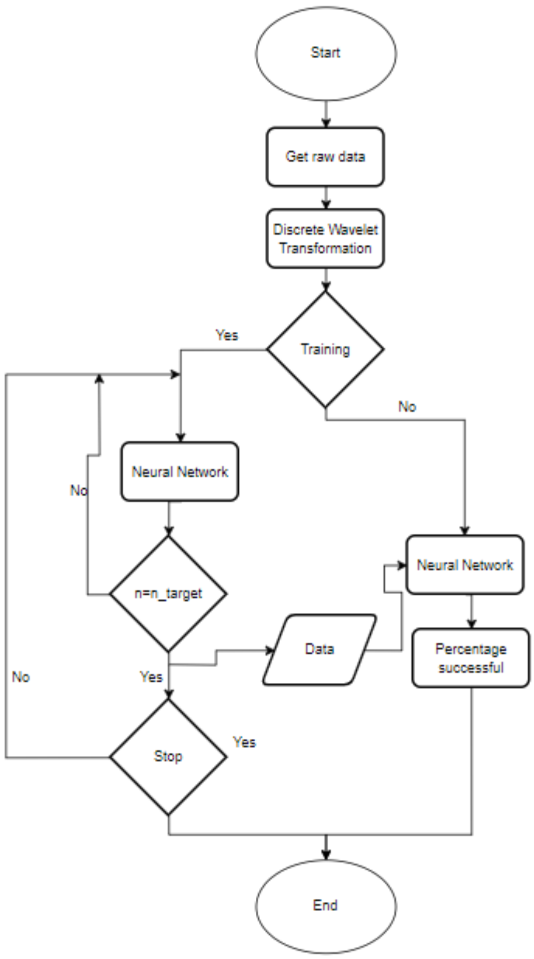
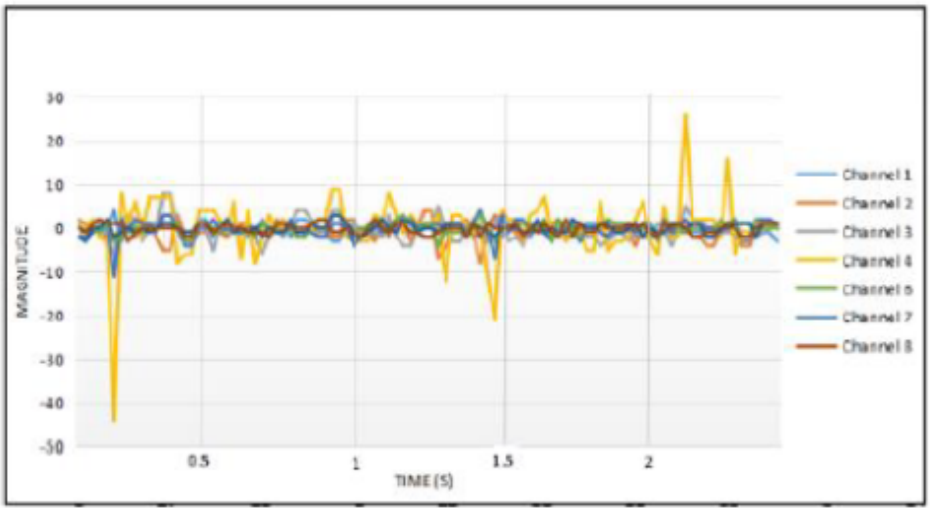


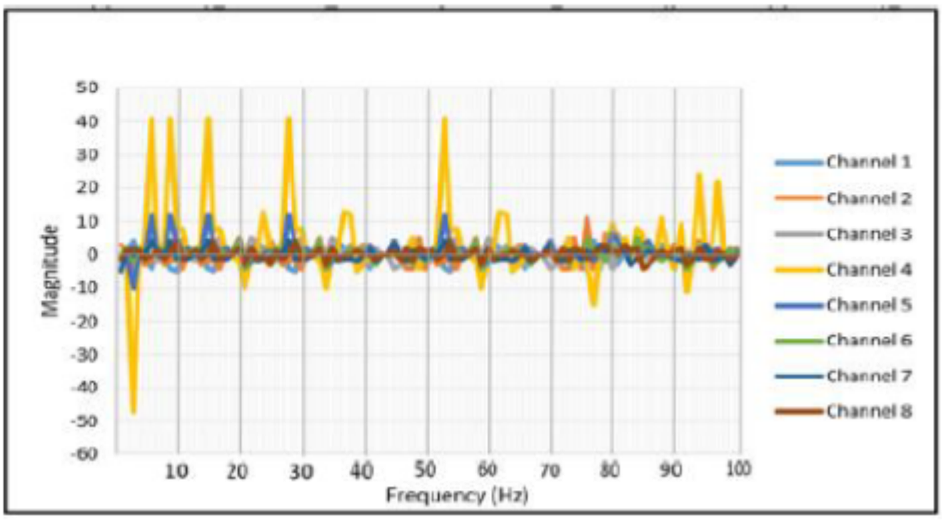
Fig. 4. Flow chart of the system

3 Results and Discusion

This section will focus on the experiments' results and discuss them. Signals from the subjects are saved in txt file. Those signals are then transformed to DWT. Figure 5a shows the raw signal from the eight EMG sensors in time domain for a relax gesture from one subject. In Figure 5b, the graphic of the signal DWT results from the raw signal.



(a)



(b)

Fig. 5. (a) raw signal (b) the DWT signal of the relax gesture

Signal DWT from three subjects with eight gestures of the fingers becomes the input of the Neural Network algorithm. We used two hidden-layer Neural Networks. One hundred input nodes, twenty-six first hidden layer nodes, twenty nodes of the second hidden layer, and eight output nodes are the Neural Network's composition. For the training phase, the iteration was set to 8000 iterations. With this iteration, the error is obtained 0.0001345.

Afterwards, the tests phase was done with the weights of the nodes obtained from the training phase. All the subjects were asked to move their hand. They do each gesture 100 times. Table 1 shows the success rate results for each gesture and subject.

Table 1. Table title. Table captions should always be positioned *above* the tables.

Gestures	Subject 1	Subject 2	Subject 3	Average
Relax	86.	82	85	84.33
Open	90	85	86	87
Close	92	82	88	87.33
Thumb	83	81	79	81
Index	79	75	72	75.33
Middle	77	69	78	74.67
Ring	70	67	68	68.33
Pinkie	79	79	83	80.33
Average	82	77.5	79.88	79.79

From Table 1, the average success for all subjects and gestures is 79.79%. Close gestures have the highest percentage of success, and the ring finger gesture is the lowest percentage of the system enabled to recognize. This situation might happen because the ring finger gesture almost uses the same muscle as the index finger movement. Moreover, close motion is the highest because most of the muscles are contracted, so it will differ from other gestures.

4 Conclusions

This system is capable of identifying the poses of the subject's fingers. Results show that the percentage of this system is 79.79% to acknowledge gestures. In the future, this system will be implemented for controlling hardware.

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