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Implementation of a Telerobotic Application with Gesture Recognition from EMG Signals

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Abstract: Telerobotic is the area of robotics concerned with remote-controlling a robot regardless barrier between the user and the robot in the environment. The human operator at the local site can control the robot using the Myo armband attached to the hand as an input device. The robot in the remote site, which is physically separated from the operator, could be controlled by the operator. As a gesture controller, the armband would process the electromyographic (EMG) muscle activation signals and send them into a State-of-the-art Deep Learning model for recognizing gestures in multi-channel time series. Artificial Neural Networks and Deep Neural Networks with five-time domain features were used for classifying the EMG data. The output from the model converted into a command for the robot to move in its workspace. As a result of the study, Artificial Neural Networks model with waveform length (WL) feature gave the best result with 92.52 percent training accuracy and 96.58 percent in test accuracy. The robot implemented in the controller moved between 0.5 to 1-second after the operator moves his hand.

Keywords: Telerobotic; EMG; Robotic; Deep Learning

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1. Introduction

Telerobotics is perhaps one of the earliest aspects of robotics. Literally meaning robotics at a distance, it is generally understood to refer to robotics with a human operator in control or human-in-the-loop. Any highlevel planning, or cognitive decisions are made by the human user, while the robot is responsible for their mechanical implementation. Herein the term tele, which means distant, is generalized to imply a barrier between the user and the environment. This barrier is overcome by remote-controlling a robot at the environment. Besides distance, barriers may be imposed by hazardous environments or scaling to very large or small environments. All barriers have in common that the user cannot (or will not) physically reach the environment. While the physical separation may be very small, with the human operator and the robot sometimes occupying the same room, telerobotic systems are often at least conceptually split into two sites: the local site with the human operator and all elements necessary to support the system's connection with the user, which could be joysticks, monitors, keyboards, or other input/output devices, and the remote site, which contains the robot and supporting sensors and control elements Niemeyer et al. (2008).

Myo armband is a wearable technology provided with eight electromyographic (EMG) electrodes, a gyroscope, an accelerometer, and a magnetometer Tepe and Demir (2020) Visconti et al. (2018), and it is used in the local site with the human operator as an input device. The Schunk LWA 4P Power Lightweight Arm is a robotic arm platform with four degrees of freedom used in the remote site ROS (2022).

The armband would be attached to the human operator's hand as a gesture controller and processes the electromyographic (EMG) muscle activation signals. The signal from

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electromyographic (EMG) proceeds by State-of-the-art Deep Learning for recognizing gestures in multi-channel time series. The Artificial Neural Network and Deep Neural Network models Dolopikos et al. (2021) with five time-domain-based learning features (root mean squire (RMS), mean absolute value (MAV), zero crossing (ZC), waveform length (WL) and slope sign change (SSC)) Tepe and Demir (2020) are used for classifying the EMG data. The output from the model would be converted into a command for the robot to move in its workspace. The command will contain the head protocol, coordinate (x, y, z), and speed ROS (2022).

This study aims to implement telerobotics using a Myo armband as a controller by reading EMG signals of human muscle activation to control a robotic arm. The EMG signals would be classified using state-of-the-art Deep Learning in multi-channel time-series processing.

2. Methods

2.1. Data Collection

Data was collected using Myo Armband with a Bluetooth adapter connected to a computer. The connection is attained using Myo Python API, which enables the device's SDK and allows Python to access the armband. Python wrapper records forearm EMG data produced by muscle activity when executing a gesture for 60 seconds Dolopikos et al. (2021). Each EMG sensor in the Myo armband will read muscle activity as a signal that streams at 200Hz Dolopikos et al. (2021) Bhatti (2019) Colli Alfaro and Trejos (2022) and represents an array containing eight integer values. The data from a single measurement session would save in a single CSV file with Unix Timestamp in every column.

Fifteen people will participate in the data collection (9 males and six females). For each person would wear the armband on their right forearm. The measuring procedure started after a brief demonstration of one of the required defined gestures: a closed fist Dolopikos et al. (2021), spread open fingers Dolopikos et al. (2021), and moving hand in each direction (up, down, left, right) Visconti et al. (2018). The subject was then instructed to perform this gesture repeatedly for 60 seconds, and to minimize the impact of random errors, five different repetitions per gesture were executed Visconti et al. (2018). Every person performed two different gestures and moved the hand for five minutes each.

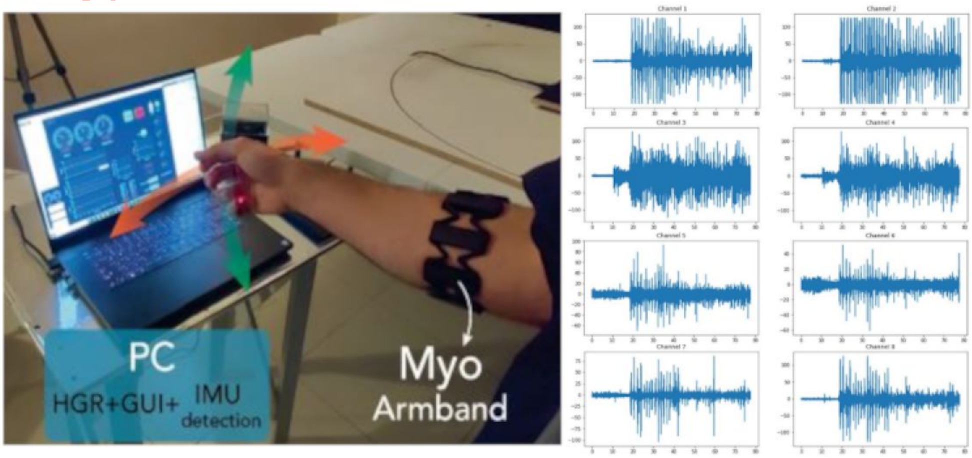

Figure 1. Data collection obtained from people used Myo Armband.

2.2. Data Pre-Processing

All CSV files would be checked for missing values, NaNs, or any measurement errors would be removed from the files. Adaptive thresholding would reduce a certain level of noise that can interfere with the analysis. Only a positive value would be used in the analysis; therefore, the EMG signal would be rectified. It is crucial to transform the data into the desired format to make the machine learning process easy.

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2.2.1. Data Cleaning

During the data collection process, the participant's hands were held still for more than one second before making the defined gesture, which could create possible errors in the analysis. An adaptive threshold Kang et al. (2020)Kaur et al. (2018) was used to detect the activation of the EMG signal by estimating the onset/offset points, and the "rest position" value in the data was removed.

2.2.2. Rectification

Raw EMG readings typically range from -128mV to +127mV for each timestamp and are highly oscillatory Dolopikos et al. (2021). By taking the absolute of all EMG values (all negative values become positive), the positive and negative values didn't cancel out when calculating the mean of EMG values. Because for analysis, it is easier if the EMG signal were rectified into only positive values McKiernan (2021).

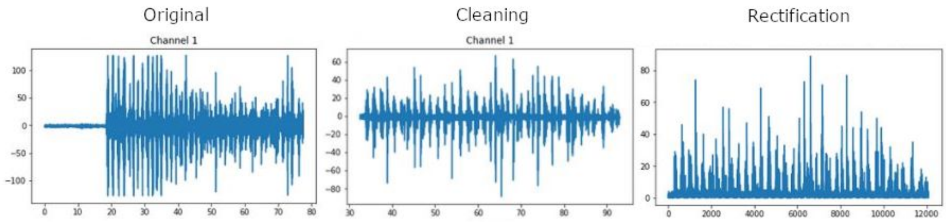

Figure 2. EMG signal processed by rectification.

2.2.3. Feature Extraction

Raw usage of the collected EMG data is not beneficial for machine learning due to the data's stochastic nature. EMG data, as previously mentioned, are bioelectric signals that are non-stationary, non-linear, and of random nature Dolopikos et al. (2021). The sliding windows method was used to segment time series data into a collection of short pieces (0.5 seconds). The time-domain-based feature was extracted from each window of the EMG data. These were: root mean squire (RMS), mean absolute value (MAV), zero crossing (ZC), waveform length (WL), and slope sign change (SSC) Tepe and Demir (2020).

$$\mathrm{WL} = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \quad (1) \qquad \mathrm{MAV} = \frac{1}{N}\sum_{n=1}^{N} |x_n| \quad (2)$$

$$\mathrm{ZC} = \sum_{n=1}^{N-1} [\mathrm{sign}(x_n * x_{n+1}) \cap (x_n - x_{n+1})], \quad \mathrm{sign}(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (3)$$

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \quad (4)$$

$$\mathrm{SSC} = \sum_{n=2}^{N-1} f[(x_n - x_{n-1}) * (x_n - x_{n+1})], \quad f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (5)$$

Figure 3. The time-domain-based feature used in feature extraction.

2.3. Classification

First, we randomly divided the data into the training and test sets that contained an equal amount of data. Artificial Neural Networks Colli Alfaro and Trejos (2022)Shterev et al. (2022) and Deep Neural Networks Shterev et al. (2022)Chandra et al. (2021) were used to classify. Based on experimental tuning results Dolopikos et al. (2021), for ANN, 20 neurons were used for a single-layer model because it provided a competitive advantage over a model with smaller neurons, and there was no increased performance with higher neurons. The set of optimized parameters used for the Multilayer Perceptron was an L-BFGS solver, 20 neurons, and a 0.1 learning rate.

The DNN consists of five hidden layers with the ReLU activation function. The five layers consisted of 206, 226, 298, 167, and 36 neurons, respectively. As the classification problem of this work is a multiclass one, a softmax activation function is used, taking place at the last layer of the network with 5 neurons. The model used a small random number as an initialized weight for the EMG dataset Dolopikos et al. (2021). ANN and DNN were built with Keras in Python 3.10 and trained on RTX 3080 Ti.

2.4. Robot Control

Post-processing converts the classified gesture into the command for the robot. The command contains the head protocol, coordinate (x, y, z), and speed. These commands are used to instruct the robot to move in its workspace. For this experiment, we use a Schunk LWA 4P robot with six degrees of freedom which can be operated and integrated with mobile handling. This lightweight arm was chosen as it was designed with three integrated Powerball modules and a battery, and it has an SDH-3 finger hand from SCHUNK ROS (2022).

3. Results

This section presents our experiment result, where we tried all extracted features with both ANN and DNN. The waveform length (WL) feature can perform better with 92.52 percent training accuracy and 96.58 percent in test accuracy for ANN with multilayer perception and 90.30 percent training accuracy, and 92.15 percent accuracy for DNN with random weight. The completed result is shown in Table 1 and for further analysis we also present confusion matrices for every classes for the best-performing model in Table 2.

Feature	Classifier			
	ANN (Multilayer Perceptron)		DNN (Random Weight)	
	Training Accuracy (%)	Test Accuracy (%)	Training Accuracy (%)	Test Accuracy (%)
RMS	89.02	94.58	82.81	89.82
MAV	90.48	91.10	82.81	89.82
ZC	45,32	49,89	48,57	51,10
WL	**92.52**	**96.58**	**90.30**	**92.15**
SSC	41.25	44,50	40,10	42,90

Figure 4. Model performance with different features.

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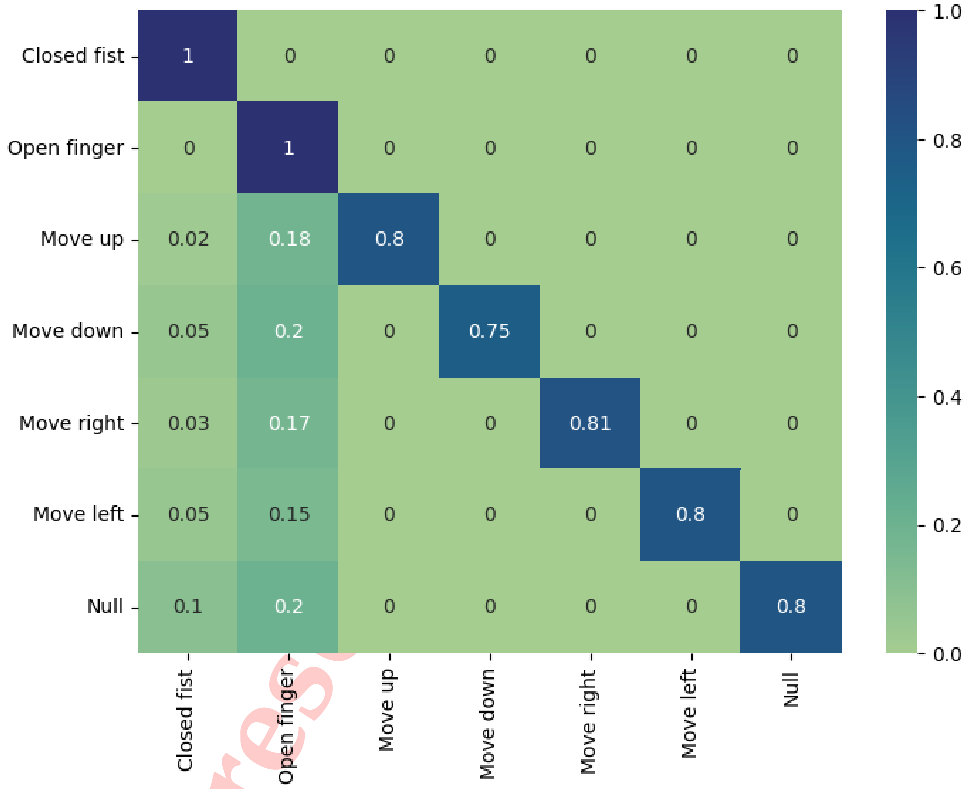

Figure 5. Confusion matrix for ANN (Multilayer Perceptron) classifier with waveform length (WL) feature.

After the classification process, we applied the model that has been trained to the controller application. The operator stands by using the Myo armband in the right hand, and the app will receive the signal from the armband in real-time. After that, the model performs the classification process of the signal and provides class predictions before the application converts it into coordinate points (x, y, z) for the robot. The operator would make two hand gestures (closed fist and spread open finger) and four hand movements (up, down, left, right). When the observation process was carried out, it was found that there was a time difference between the hand movements of the operator and the movements of the robot. When the operator's hand moves, the robot moves 0.5 to 1-second after.

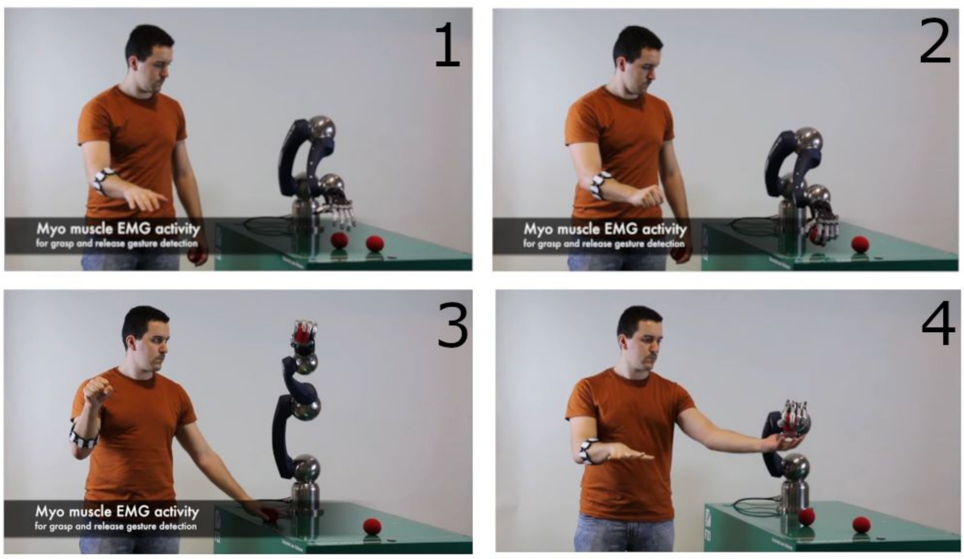

Figure 6. Experiment resulted robot movement by user command.

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4. Conclusions

In this paper, we have implemented an Artificial Neural Networks and Deep Neural Networks model with five time-domain-based learning features (root mean squire (RMS), mean absolute value (MAV), zero crossing (ZC), waveform length (WL) and slope sign change (SSC) to classified the EMG signal. We know that Artificial Neural Networks models combined with waveform length (WL) feature can perform better with 92.52 percent training accuracy and 96.58 percent test accuracy. Although we use the best model to do classification, the robot still can't mimic operator hand movement in real time because there is a 0.5 – 1 second delay. Although we can't make a robot mimicry the operator in real-time, we can achieve the goal of this study. The future study aims to find a method to reduce the delay between the operator and robot movement so that the robot can mimic the operator in real-time.

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