
*Article*

# A Prototype of MyoWare (Electromyography Muscle Sensor) for Measuring People's Muscle Strengths

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**Abstract:** Human-Computer Interaction (HCI) becomes a solution to help humans connect with computers. Research and tools related to HCI have been developed by many researchers. HCI is able to help humans connect between humans and computers and humans with humans at a considerable distance. One of HCI model is applied to the MyoWare tool that can capture hand muscle movements using an electromyograph (EMG) sensor. This article describes how to assemble and identify the raw data generated from the MyoWare tool. Using MyoWare on the hand could produce EMG data output. MyoWare only used the EMG sensor and generated data in the form of Envelope EMG and Raw EMG which differed in scale and size. This required a extraction features process to make the data uniform. This study uses the Moment Invariant method to extract features and min-max to normalize each data generated on the MyoWare sensor. Testing was done by doing simple hand movements. The test results showed that the differences in gestures were recognized well even though they were performed in different positions.

**Keywords:** HCI; Hand Gesture; Myo Ware; Moment Invariant, Min-Max

## 1. Introduction

The development of technology in the field of Human-Computer Interaction (HCI) has a tremendous impact, especially in the field of hand gesture recognition. Nowadays, research on hand gesture recognition such as virtual reality, robotics, computer games (animated), remote control, the introduction of sign language, and more has been done in various fields. The development of these technologies enables people to interact and build good communication between humans and machines [1].

In addition, the development of computerized hand gesture recognition is an important requirement in the industrial era 4.0, especially during the COVID-19 pandemic. The pandemic has made people more concerned about health. Hence, many researchers have conducted several studies and approaches to health surveillance using hand gesture recognition technology. At this time, hand gesture recognition technology is very closely related to daily activities. It is a useful solution to knowing and monitoring the state of human bodies.

There are various developments of HCI technology for hand gesture recognition, such as the use of smartwatches to determine the heart rate in the blood vessels on the wrist [2], The use of Myo Armband aims to assist deaf communication using a sign language [3], and hand and arm strength recognition tools are developed to monitor the condition of users and physiotherapy patients [1]. The various types of approaches in hand gesture recognition technology aim to help humans to connect and control their health through HCI.

HCI technology in the health sector have been researched, especially in post-stroke patients who seek for treatment or therapy [4]. Previous research found that muscle tone in post-stroke patients increased and caused muscle spasticity. Muscle spasticity causes stiffness, pain, and difficulty moving, and it will affect the normal movement of post-stroke patients [5]. In addition, increased muscle tone is a sign to not optimal therapy in post-stroke patients.

Based on the issues, a prototype device was assembled in the form of an electromyograph (EMG) sensor to help treat post-stroke patients [6]. The novelty of this research is how we can measure and predict the movement muscle on human arm to help stroke patients. The prototype of the device is used to improve the quality of spasticity treatment by finding the pattern of the EMG sensor performance[4]. However, at this stage, this study aimed to describe the tool development process and measure muscle strengths in a normal human arm. This study also aimed to create a tool that can be used in future research on post-stroke patients.

## 2. Materials and Methods

This paper aimed to find out the performance of the MyoWare raft tool and the EMG sensor data output . It will also inform the basis for further research on a technology for detecting muscle tone with easy use by therapists and patients' families. In this section, a device design of MyoWare muscle sensor kit and its evaluation were explained along with how it affects hand movements.

### *2.1. Related Work*

A. F. Ruiz-olaya [7] predicted that gesticulation can be detected using pattern recognition through the biological signal from the EMG sensor. This study compares two experiment results of hand gesture recognition algorithm based on the EMG sensor. That algorithm used information-generated kinetics, and EMG data were better for classifications of five hand movements rather than the use of EMG data.

M. Sathiyanarayanan [1] demonstrated the use of the MYO armband for physiotherapeutic treatment. This study analyzed the EMG sensor on MYO diagnostics to detect abnormalities in hand movements. The test was conducted on 24 medical students using the SUS questionnaire. This study was an alternative way to support the interactive physiotherapy analysis and help better understand the entire myocardial system with early diagnosis.

### *2.2. Design System*

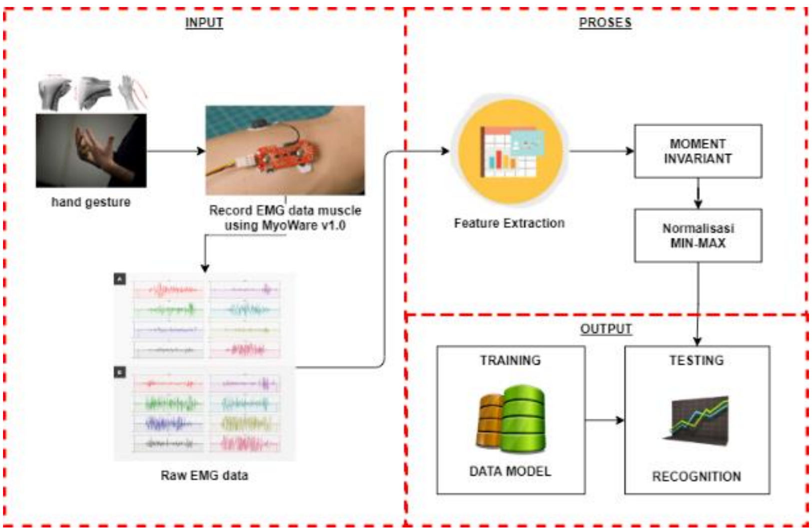


**Figure 1.** Design Hand Gesture Recognition System

Figure 1 shows the system design. This study used a moment invariant feature which is an extraction method and min-max normalization

### 2.3. MyoWare Muscle Sensor Kit

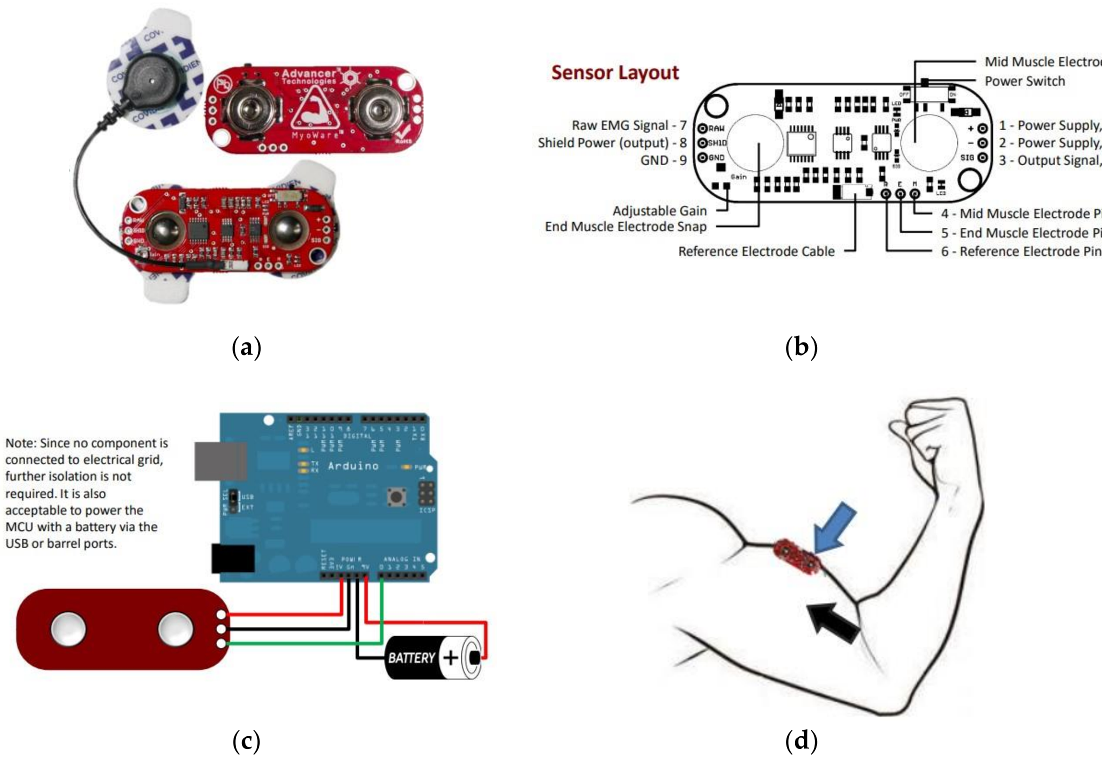


**Figure 2.** (**a**) MyoWare muscle sensor tools; (**b**) Sensor Layout; (**c**) Setup Configuration MyoWare on Arduino; (**d**) MyoWare position when use on bicep.

Muscle activation via electric potential or electromyography (EMG) has traditionally been measured for diagnosis of neuromuscular disorders in medical research [8]. However, with the advent of ever shrinking yet more powerful microcontrollers and integrated circuits, EMG circuits and sensors have contbuted to prosthetics, robotics, and other control systems [9][10][11][12].

### 2.4. Hand Gesture Experiments

These experiments used some hand gestures following dynamic movements that received different treatment. This step aimed to identify patterns, the influence of the movement against the existing sensors on the MyoWare and feature extraction. Dynamic movement is a movement of the right and left (radial-deviation), up and down (flexion-extension), and pronation-supination. The movement was used to measure speed, direction, and position contained in MyoWare as shown in Figure 3.

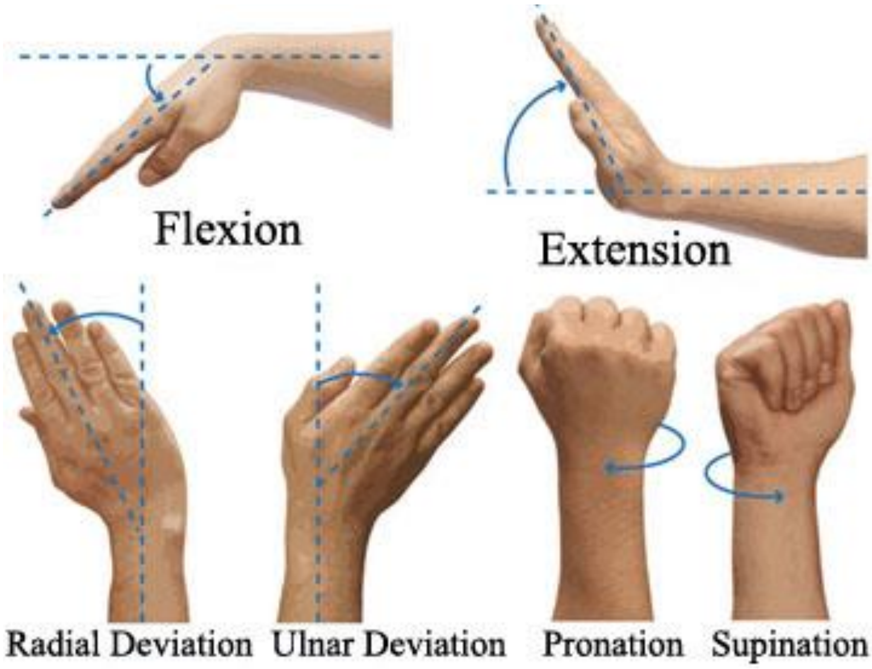


**Figure 3.** Hand gestures used in the experiment

### 2.5. Proposed Method

The measurement results of hand movement showed nonuniformity sensor data both in scale and size. When nonuniform data were used directly for the recognition process, a lot of errors happened. Errors were caused by ambiguous movement, sensor failure, short measurement, or early measurement failures [13] The data showed inconsistent sizes and scales. Signal data were not easy to translate, and the extraction process was required to be a feature vector.

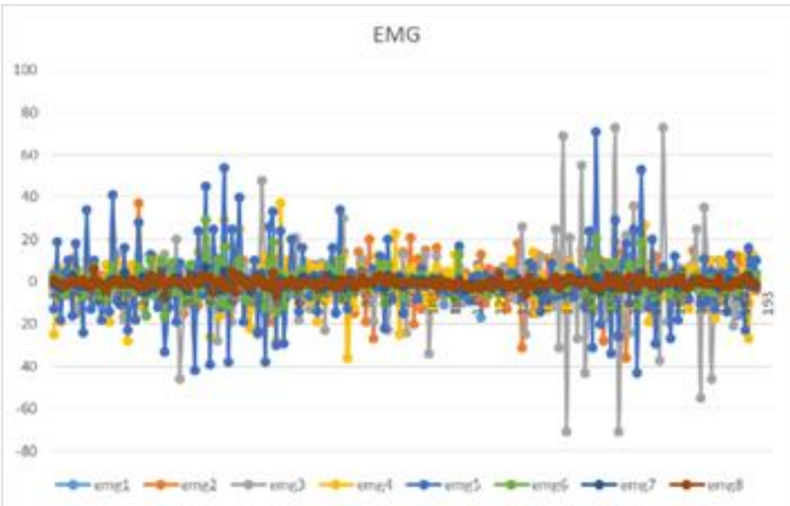


**Figure 4.** Raw Data EMG Sensor

Figure 4 shows the chart patterns of muscle contraction obtained from the EMG sensor. The data were raw data that required treatment prior extraction into feature vectors. In mathematical terms, the raw data are shown in the formula (1).

EMG sensor Formula

$$\boldsymbol{D_m} = \sum_{i=1}^{n} \begin{bmatrix} v_{emg1_i} & v_{emg2_i} & \cdots & v_{emg8_i} \\ \vdots & \vdots & \vdots & \vdots \\ v_{emg1_n} & v_{emg2_n} & \cdots & v_{emg8_n} \end{bmatrix} \quad (1)$$

Where:

$\boldsymbol{D_m}$ = data from EMG sensor
$\boldsymbol{v}$ = measurement value
$\boldsymbol{n}$ = data size

2.5.1. Min-Max Method

The sensor data produced were not consistent with the scale, thus requiring the process of normalization. This study used the Min-Max method for data normalization.

$$newdata = \frac{1}{\max - min} x(data - min) \quad (2)$$

Where:
$max$ = maximum value of $v$
$min$ = minimum value of $v$

This method can exert the balance between the values of the comparison data. No data were dominant over others. Data normalization was performed because the data obtained from EMG generated 2-dimensional patterns with different data values [14].

2.5.2. Moment Invariant Method

Extraction feature in this study was invariant moment, a scalar value that captures a significant feature. This value provided object's characteristics that uniquely represent the shape. Using the moment invariant method, this study aimed to describe the object with invariant, insensitive to a certain deformation. As a result, it could provide enough power to recognize objects from different classes [15]. The next process was to form feature vectors by calculating the mean, median, standard deviation, and skewness of each axis in the sensor data.

$$\overline{X}_{D_{(m)}} = \frac{\sum_{i=1}^{j} D_{(m)}}{n} \quad (3)$$

$$Me_{D_{(m)}} = \frac{(n+1)}{2} \quad (4)$$

$$S_{D_{(m)}} = \sqrt{\frac{\sum_{i=1}^{j} (v_i - \overline{X})^2}{n-1}} \quad (5)$$

$$S_{k_{(m)}} = \sqrt{\frac{\sum_{i=1}^{j} (v_i - \overline{X})^3}{n-1}} \quad (6)$$

Where:
$n$ = data size
$\overline{X}_{D_{(m)}}$ = mean for each data sensor
$Me_{D_{(m)}}$ = median for each data sensor
$S_{D_{(m)}}$ = standard deviation for each sensor
$S_{k_{(m)}}$ = skewness for each data sensor

The results of the calculation (3), (4), (5), and (6) produced a data model with 84 bins for hand gestures.

$$DM_m = \begin{bmatrix} \overline{X}_{emg1} & \overline{X}_{emg2} & \cdots & \overline{X}_{emg8} \\ Me_{emg1} & Me_{emg2} & \cdots & Me_{emg8} \\ Sd_{emg1} & Sd_{emg2} & \cdots & Sd_{emg8} \\ Sk_{emg1} & Sk_{emg2} & \cdots & Sk_{emg8} \end{bmatrix} \tag{7}$$

The next step was to measure whether the feature vectors already represented a hand gesture or not. The calculation of the formulas (8) and (9) showed sensitive data across various hand gestures

$$R = \frac{\sum_i^j (DM_{(a,g,o,e,m)_i} - DM_{(a,g,o,e,m)_{i+1}})}{n} \tag{8}$$

$$Robust = \begin{cases} 1; & -1 < R < +1 \\ 0; & else \end{cases} \tag{9}$$

Where:
$R$ = differential of data
$DM_{(m)}$ = feature vector

## 3. Results and Discussion

### *3.1. Flexion-Extension*

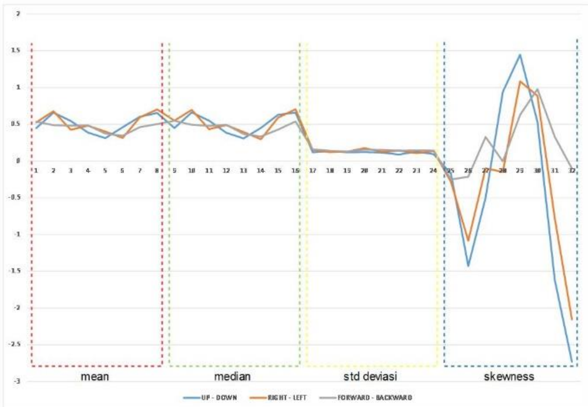


**Figure 5.** Feature vector for EMG flexion-extension

Figure 5 shows the feature vector of each sensor. This study found differences in the patterns of the movements. The feature vectors could identify different movements that could be robust to their positions.

### *3.2. Radial-Ulnar Deviation*

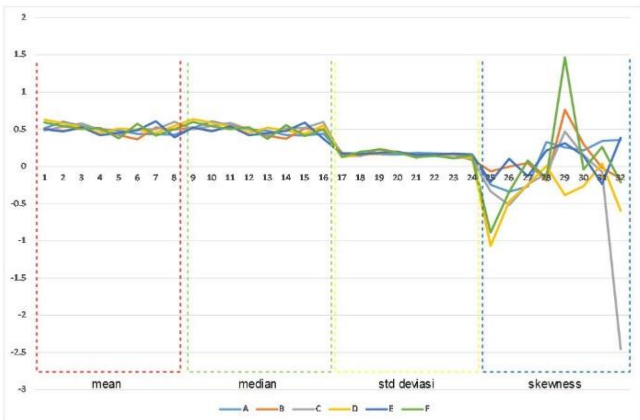

**Figure 6.** Feature vector for EMG radial-ulnar deviation

Figure 6 shows that the data produced different patterns. The difference in movement affects the data patterns.

### *3.3. Pronation-Supination*

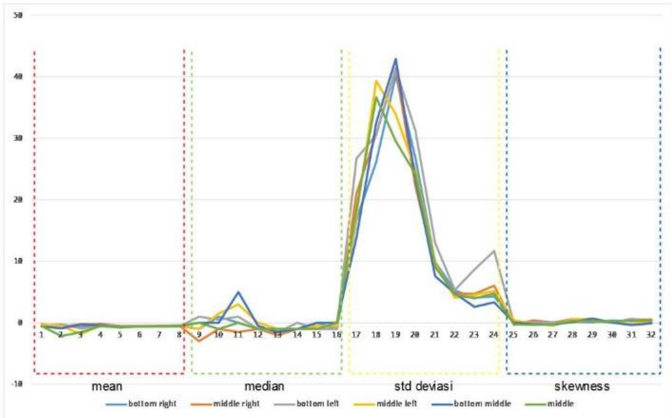


**Figure 7.** Feature vector for EMG data pronation-supination

Figure 7 shows that the data generated the same patterns. The feature vector could recognize the same movements although the position and direction were different.

## 4. Conclusions

Based on the method proposed and variations in hand motion, MyoWare recognized movements whose positions and directions were the same, except movements (robust). This technology also recognized the same hand movements in different directions. The use of the moment invariant method as a feature extraction was still powerful enough for the technology to recognize robust hand movements. In the next development, MyoWare and the moment invariant method can be used to help treat post-stroke patients through hand movement recognition.

## 5. Patents

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## References

1. M. Sathiyanarayanan and S. Rajan, "MYO Armband for physiotherapy healthcare: A case study using gesture recognition application," *2016 8th Int. Conf. Commun. Syst. Networks, COMSNETS 2016*, pp. 1–6, 2016, doi: 10.1109/COMSNETS.2016.7439933.
2. D. Iakovakis and L. Hadjileontiadis, "Standing hypotension prediction based on smartwatch heart rate variability data: A novel approach," *Proc. 18th Int. Conf. Human-Computer Interact. with Mob. Devices Serv. Adjunct,*

*MobileHCI 2016*, pp. 1109–1112, 2016, doi: 10.1145/2957265.2970370.

3. A. Rahagiyanto, A. Basuki, R. Sigit, A. Anwar, and M. Zikky, "Hand Gesture Classification for Sign Language Using Artificial Neural Network," *ICSEC 2017 - 21st Int. Comput. Sci. Eng. Conf. 2017, Proceeding*, vol. 6, no. Mi, pp. 205–209, 2018, doi: 10.1109/ICSEC.2017.8443898.
4. G. E. J. Suyoso, V. Vestine, and A. Rahagiyanto, "A Review of Muscle Tone Alteration on Post Stroke Patient," *Proc. 2nd Int. Conf. Soc. Sci. Humanit. Public Heal. (icosh. 2021)*, vol. 645, no. Icoship 2021, pp. 249–253, 2022, doi: 10.2991/assehr.k.220207.042.
5. X. Zhang, X. Tang, X. Zhu, X. Gao, X. Chen, and X. Chen, "A regression-based framework for quantitative assessment of muscle spasticity using combined emg and inertial data from wearable sensors," *Front. Neurosci.*, vol. 13, no. MAY, 2019, doi: 10.3389/fnins.2019.00398.
6. D. M. Nareva, "Hemiparesis: Kelemahan Otot pada Salah Satu Sisi Tubuh," *ALODOKTER*, 2021. https://www.alodokter.com/hemiparesis-kelemahan-otot-pada-salah-satu-sisi-tubuh (accessed Apr. 08, 2021).
7. A. F. Ruiz-Olaya, M. Callejas-Cuervo, and A. Milena Perez, "EMG-based Pattern Recognition with Kinematics Information for Hand Gesture Recognition," *20th Symp. Signal Process. Images Comput. Vis. Conf. Proc. , Bogotá, Colomb.*
8. R. Suhaimi *et al.*, "Analysis of EMG-based muscles activity for stroke rehabilitation," *2014 2nd Int. Conf. Electron. Des. ICED 2014*, pp. 167–170, 2014, doi: 10.1109/ICED.2014.7015792.
9. C. S. Klein, S. Li, X. Hu, and X. Li, "Editorial: Electromyography (EMG) Techniques for the Assessment and Rehabilitation of Motor Impairment Following Stroke," *Front. Neurol.*, vol. 9, 2018, doi: 10.3389/fneur.2018.01122.
10. T. Bintang Dewantoro, R. Sigit, H. Yuniarti, Y. D. Prawitri, F. A. Pamudyaningrum, and M. Ilham Awal, "Implementation of Myo Armband on Mobile Application for Post-stroke Patient Hand Rehabilitation," *Proceeding Electr. Eng. Comput. Sci. Informatics*, vol. 5, no. 5, pp. 455–450, 2018, doi: 10.11591/eecsi.v5i5.1585.
11. S. Sharma, V. Steuber, and F. Amirabdollahian, "Assessing the Impact of Muscular Fatigue on Myoelectric Signals Using Myo Armband," *ACHI 2019 Twelft Int. Conf. Adv. Comput. Interact.*, no. c, pp. 159–164, 2019.
12. C. K. Piyus, V. A. Cherian, and S. Nageswaran, "EMG based FES for post-stroke rehabilitation," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 263, no. 5, 2017, doi: 10.1088/1757-899X/263/5/052025.
13. M. Kumar, D. P. Garg, and R. A. Zachery, "A method for judicious fusion of inconsistent multiple sensor data," *IEEE Sens. J.*, vol. 7, no. 5, pp. 723–733, 2007, doi: 10.1109/JSEN.2007.894905.
14. Y. Makino, S. Ogawa, and H. Shinoda, "EMG sensor integration based on two dimensional communication," *Proc. INSS 2008 - 5th Int. Conf. Networked Sens. Syst.*, p. 257, 2008, doi: 10.1109/INSS.2008.4610851.
15. J. Flusser, T. Suk, and B. Zitová, *Moments and Moment Invariants in Pattern Recognition*. 2009.