# Applications of Probability Density Function for Instrumented Wheelchair Control Based on EMG Signals from Arm and Forearm Muscles

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| ARTICLE INFO | ABSTRACT |
|---|---|
| **Article history:** | Patients with muscle weakness or stroke continue to use wheelchairs as essential mobility aids. Some stroke patients who have restricted movements of their hands due to muscle weakness. As an alternative to propel wheelchair more easily, an instrumented wheelchair that has Power Assist System (PAS) with Electromyography (EMG) interface would help the patients by providing additional forces. The device is consisting of Myoware Muscles sensors, Arduino board, motor driver and installed with machine learning Probability Density Functions (PDF) classifier to recognise hand movement pattern to instruct PAS to move forward or stop. 3 participants volunteered in this study to evaluate the classification accuracy of the device by recording EMG signals from Biceps Brachii (BIC), Triceps Brachii (TRI), Flexor Digitorum (FIX) and Extensor Digitorum (EXT) muscles. PDF showed a good response by having average classification accuracy as high as 97.85% and lowest is 89.99%. This finding shows the capability of PDF classifiers in EMG applications. |
| **Keywords:** Electromyography; probability density function; Arduino; instrumented wheelchair; Myoware | |

## 1. Introduction

Wheelchair is a very important tool for the disabled persons who are unable to move the leg muscles to manoeuvre around [1]. Electrical wheelchair usage is the most appropriate way to assist them in getting around. For stroke patients who are unable to move their wheelchairs using joysticks, special steering devices must be used [2]. To enable patients to perform their activities independently, motorised wheelchair is one of the automatic solutions [3,4]. However, the wheelchair users who has an impaired hands and unable to move their hands to control and to use the joystick for electric wheelchair remains a problem [5]. Based on findings of a survey conducted by the Product Development Team of the Mechanical Engineering Department of ITS in various locations, including hospitals and institutions for the disabled [6], it was discovered that a wheelchair that is assistive and responsive is greatly desired by people with disabilities. This is due to their lower satisfaction with the current state of wheelchairs, which are 58.3% for incomplete, 25% for less comfortable and 4.1% coming from difficult to use. In addition, 12.6% said that manual wheelchairs

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no longer enable them to carry out activities like regular individuals. In order to assist users with the constraints indicated above, an alternative controls method for electric wheelchairs should be created [7].

In medical, electromyography (EMG) is one of the methods to monitor muscle activity and record muscular electric signals has been widely applied [8]. EMG signal is also used to identify any disorders of nerve and functions of muscle of the patient. Furthermore, EMG may detect disorder that shown by signal weakness of the muscles. EMG also is being used to interact with humans and computers. For example, applications that replace human organ functions, such as games industry and robot-based security [9]. One of the products integrated developments of human's interaction and communication with computers is MYOWARE developed by Advancer Technologies [10]. MYOWARE muscle sensor is an EMG sensor that able detect electrical signals that are transmitted by the nervous system when the muscle contracts and it's called as Motor Unit Action Potential (MUAP) [11,12]. The output data of the EMG sensor is anticipated to be processed using the Probability Density Function (PDF) algorithm and analysed result is used to control the movement of the wheelchair according to user's desires [13,14].

Aims for this study is to recognize the pattern of MUAP to match with the desires of user either to propel forward or to prepare their hands to ready for next movement. Output of these patterns' classification would activate the DC motors to assist them to move around with the wheelchair.

## 2. Methodology
### 2.1 Subjects

Participants in this study are 3 healthy with no disability males. All the participants are students at the University Kuala Lumpur (UniKL) and their details as age, height, weight, and propulsion data as listed in Table 1. The average age is 22 years, height 166.33 cm and weight 61 kg. The participants have totally had no experience in using the EMG interface control instrumented wheelchair. A demonstration session on the pattern of hand movement and experiment timeline are explained to all participants. Since they have no experience in wheelchair propulsion, training time total of 12 minutes is provided before the experiment starts [15,16]. In line with the instructions given by the university research ethics committee, they have all been provided with a letter of consent before willingly participating in this study.

**Table 1**
Details of participants

| Participant | Gender | Age (year) | Height (cm) | Weight (kg) | Average contact time (s) | Average recovery time (s) |
|---|---|---|---|---|---|---|
| 1 | Male | 20 | 156 | 49 | 1.63 | 1.76 |
| 2 | Male | 24 | 171 | 56 | 2.12 | 1.33 |
| 3 | Male | 22 | 172 | 78 | 1.13 | 1.89 |

### 2.2 Data Acquisition

Motor Unit Action Potential (MUAP) was recorded using 4 units of Myoware muscle sensors with 16 units of surface electrodes attached to an Arduino MEGA 2560 microcontroller board. The surface electrode pad is made of silver-silver chloride (Ag-AgCl). Configurations of devices used in this study as in Figure 1 and Figure 2 is the flow of sEMG signal. During wheelchair propulsion, sensors had been located on their arms to record MUAP. Before placing the surface electrodes to reduce the noise, skins of the arm had been shaved and washed with alcohol. Non-Invasive Assessment of Muscles

(SENIAM) was referred as guideline to place sensors on targeted muscles [17,18]. 4 muscles have been selected for placement of the surface electrodes that are Biceps Brachii (BIC), and Triceps Brachii (TRI) for arm. Meanwhile, Flexor Digitorum (FIX) and Extensor Digitorum (EXT) are for forearms. To store the MUAP's value to perform additional analysis, Arduino MEGA 2560 is linked to a laptop via a USB cable. As shown in Figure 1, the flowchart of Surface Electromyography (sEMG) signals from the MUAP sensors in the muscles to the activation of DC motors in Power Assistive System (PAS).
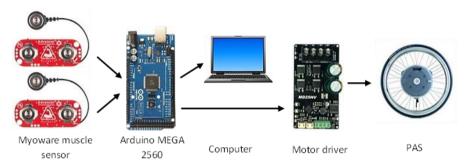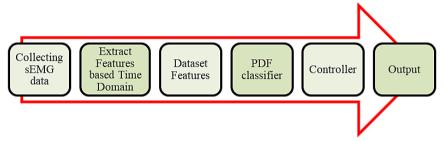


**Fig. 1.** Configurations of sEMG data acquisition device



**Fig. 2.** Flow of sEMG signal

## 2.3 Experiment Protocol

In order to place the surface electrodes, patients are asked to stand in their wheelchair and have their right hand shaved and cleaned [19,20]. The hand movement may be grouped into two stages, contact and recovery. Contact phase is when the participants grasp the push rim of wheelchair and push forward, which will prompt the wheelchair to move. Arc pattern is the selected method of hand movements. The arc pattern requires the subject to touch the push rim with his or her hands all the time. As can be seen in Figure 3, there are also various patterns such as the Single Circular, Double Circular and Semicircular [21,22]. Position of right hand moved from point A to point B. In the meantime, during the recovery phase, the patient's hand returns to the initial position in the contact phase from point B to point A. Wheelchair doesn't move during recovery phase. Tiled floor is where experiments took place.

Duration of the test is 110 seconds, comprising three stages which are data collection phase, calculation, and classification accuracy measurement, as described in Figure 4. The collection of individual data takes place in between 0 and 50 seconds, where the Probability Density Function (PDF) classifiers is trained based on data from 5 contact to 5 recovery phases. In this stage, participants must propel forward 5 times and do the hand return movement alternately. There is no wheelchair propulsion action between 50 and 60 seconds while the calculations of the MUAP's mean and standard deviation (SD) from the previous stage is being done. Then, classification accuracy

measurement takes between 60 and 110 seconds and uses the same methodology as the step of collecting individual data.
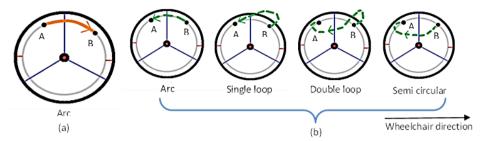


**Fig. 3.** Pattern of hand movement during wheelchair propulsion. Available patterns (a) Contact phase (b) Recovery phase
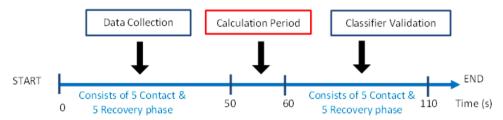


**Fig. 4.** Stages of experiment

*2.4 Extract EMG Features Based Time Domain*

Calculated Root Mean Square (RMS) and Standard Deviation (SD) of each sample at each channel, as shown in Eq. (1) and Eq. (2), respectively. Root Means Square (RMS) is a statistical feature that is applied in the typical time domain analysis approach. Then, calculate Mean Absolute Value (MAV) of each sample at each channel of sensors (Eq. (3)).

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

where N is number of data sequences and $x_n$ is value of data at index n.

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \qquad (2)$$

where σ is standard deviation, N size of population and $x_i$ is MUAP value.

$$MAV = \frac{1}{n}\sum_{i=1}^{n}|x_i - m(X)| \qquad (3)$$

where m(x) is average value of data set, n is number of data values and $x_n$ is data values in set.

Probability Density Function (PDF) is the pattern recognition classifier used in this study. It has been established that PDF can be classified with great accuracy and is capable of handling the sEMG application properly [23,24]. Figure 4 gives an equation for PDF. In order to determine which, one has higher values, PDF compares the probability of value from contact or recovery phases and applies

the PDF equation. e is a constant Euler's number which is equal to 2.71828, π is 3.14159, μ is mean, σ is SD and X is MUAP readings.

$$F(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(X-\mu)^2}{2\sigma^2}}$$
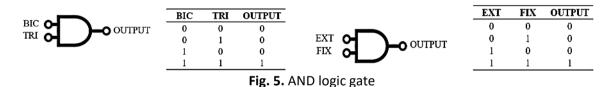(4)

where:
e = 2.171828
π = 3.14159
X = MUAP value
μ = Mean
σ = Standard deviation

## 2.5 Transverse Channel and Logic Gate System

In recognition of the MUAP pattern, activation of a power assist system that is dependent on one muscle or its call for single as threshold would result in an increased error rate [25,26]. Implementing AND logic gates philosophy as in Figure 5 is a solution to this problem. To distinguish hand movements during contact and recovery phases, not only one but sEMG signal form two muscle are used as an indication for PDF recognition of the MUAP pattern. To reduce the error rate, combination between two competing muscles such as BIC coupling to TRI and EXT coupled to FIX.



| BIC | TRI | OUTPUT |
|-----|-----|--------|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 1 | 1 | 1 |

| EXT | FIX | OUTPUT |
|-----|-----|--------|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 1 | 1 | 1 |

**Fig. 5.** AND logic gate

The PDF equation is divided into A, B, C, D and G as described in Figure 6, to be embedded into the algorithm. This is due to shorten the calculation time. Sampling rate speed will decrease with the length of the algorithm. Algorithm of PDF calculation flow as shown in Figure 7. In order to determine values of A and B, mean and SD of maximum MUAP values must be calculated earlier. C will be determined by after 60 seconds and X value is MUAP of muscles. Then, B*C is equal to D and going to be used in determining probability either higher in contact phase (Gc) or recovery phase (Gr).
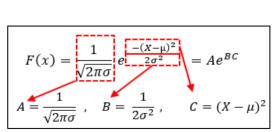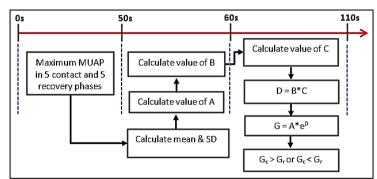


**Fig. 6.** PDF equation is divided into A, B and C



**Fig. 7.** Calculation flow of PDF by Arduino board

## 3. Results

Result on experiment for classification accuracy measurement are as below. Results are separated between sEMG signals for arm muscles (Biceps Brachii (BIC) and Triceps Brachii (TRI)) and forearm muscles (Flexor Digitorum (FIX) and Extensor Digitorum (EXT)). Black dotted lines are PDF classifiers recognition result where signal "1" is indicating that participants are propelling or pushing the pushrim forward.  Meanwhile "0" is showing participants are doing something other than pushing the pushrim forward. Result for participant 1 as Figure 8 (Bic + Tri) and (Ext + Fix). PDF classifier recognized 3 out of 5 contact phases for Bic+Tri sEMG signal. But, for Ext+Fix two times in contact phase and 1 time in recovery phase. Result for participant 2 as Figure 9. PDF classifier recognized in all 5 contact phases and once in recovery phase for Bic+Tri sEMG signal. Same things happened for sEMG signals from Ext+Fix. Figure 10 is resulting participant 3 results. For Bic+Tri and Ext+Fix, PDF recognised 4 times in contact phase and 3 time in recovery phase.
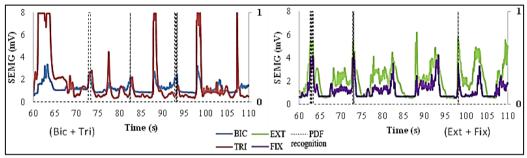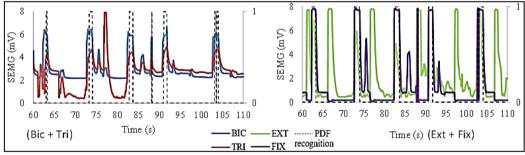


**Fig. 8.** Experiment result for participant 1



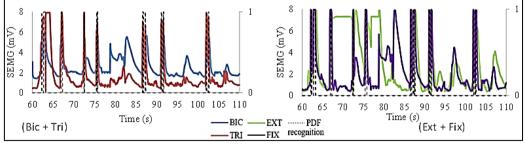**Fig. 9.** Experiment result for participant 2



**Fig. 10.** Experiment result for participant 3

Table 2 shows classification accuracy for every contact phase. Meanwhile, data for recovery phase as in Table 3. In contact phase, participant 1 and 2 have higher classification accuracy for signal from Bic+Tri. But participant 3 higher classification accuracy is coming from Ext+Fix sEMG signals.

Different trends in recovery phase can be seen in Table 3. All participant has better classification accuracy by analysing sEMG signals from Bic+Tri.

**Table 2**
Classification accuracy in every contact phase

| Participant | Muscle | Contact phase | | | | | Average |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | | 1 | 2 | 3 | 4 | 5 | |
| 1 | Bic + Tri | 87.37% | 96.94% | 88.66% | 94.62% | 87.63% | 91.04% |
| | Ext + Fix | 94.74% | 92.86% | 87.63% | 87.10% | 87.63% | 89.99% |
| 2 | Bic + Tri | 92.58% | 99.56% | 98.36% | 99.37% | 99.37% | 97.85% |
| | Ext + Fix | 93.42% | 90.13% | 90.03% | 96.07% | 90.68% | 92.07% |
| 3 | Bic + Tri | 95.01% | 89.86% | 88.02% | 95.26% | 93.26% | 92.29% |
| | Ext + Fix | 98.17% | 90.90% | 88.02% | 95.26% | 95.26% | 93.53% |

**Table 3**
Classification accuracy in every recovery phase

| Participant | Muscle | Recovery phase | | | | | Average |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | | 1 | 2 | 3 | 4 | 5 | |
| 1 | Bic + Tri | 100% | 100% | 100% | 100% | 100% | 100% |
| | Ext + Fix | 100% | 100% | 100% | 99% | 100% | 99.8% |
| 2 | Bic + Tri | 100% | 100% | 99% | 100% | 100% | 99.8% |
| | Ext + Fix | 100% | 100% | 97% | 100% | 100% | 99.4% |
| 3 | Bic + Tri | 95.96% | 94.19% | 93.55% | 100% | 100% | 96.74% |
| | Ext + Fix | 95.96% | 90.70% | 90.32% | 100% | 100% | 95.4% |

Figure 11 is a graph shows classification result for every contact and recovery phases for participant 1. In contact phase, Bic+Tri's accuracy is higher in 4 out of 5 phases and only in recovery phase 4 it's reduced to 99%. Participant 2 results as in Figure 12. Clearly can be seen that Bic+Tri's accuracy is better in all phases of contact and recovery. Meanwhile for participant 3, Ext+Fix signals have better accuracy in all contact phases but the opposite result recorded in recovery phases as in Figure 13. Comparison experiment result as in Figure 14. Average classification accuracy in recovery phases is higher to all participants compared to contact phase.
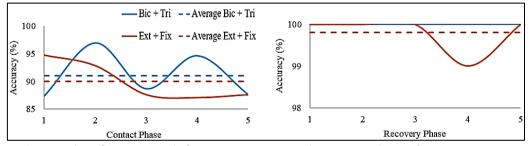


**Fig. 11.** Classification result for every contact and recovery phases for participant 1
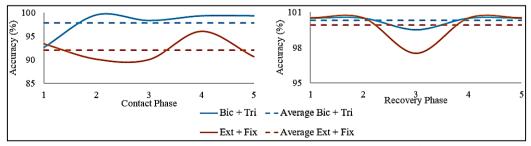


**Fig. 12.** Classification result for every contact and recovery phases for participant 2
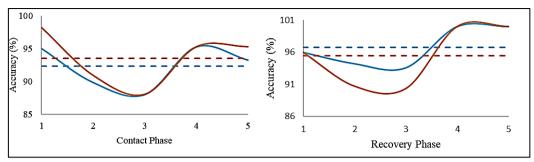
**Fig. 13.** Classification result for every contact and recovery phases for participant 3
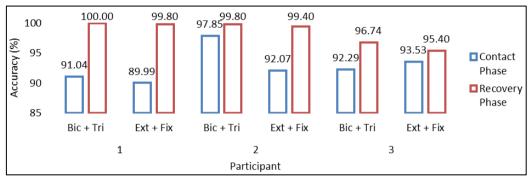


**Fig. 14.** Comparison of average classification accuracy Bic+Tri and Ext+Fix

## 4. Conclusions

Classification accuracy in recovery phase is higher than contact phase is due to no hand movement in recovery phase. There is not much spike of MUAP signals of all muscles happens at the same time. Compared to contact phase when participant's arms are pushing the pushrim forward, MUAP changes will be recorded and analysed by PDF classifier. In order to recognise the movement, signals from both targeted muscles such as Bic and Tri must have higher probability at the same time. Consequently, classification accuracy contact phases are much lower than recovery phases. As result in Table 2 and Table 3, classification accuracy signals from Bic+Tri are higher for 2 out of 3 participants. The most important things that must be considered is classification accuracy in recovery phase instead of contact phase. In recovery phase, classifier can't make any mistake in analysing hand movement in this period.

In recovery phase, wheelchair is supposedly not moving at all. The accuracy must be 100% and below that can't be considered as suitable classifier for the participant. This is because if the classifier analyses the signal and send signal "1" to the processor, DC motor in power assistive system will trigger and start to rotate. It would bring harm to the wheelchair users by moving forward without user's intentions. PDF classifier is suitable for participant 1 by using signals from Bic and Tri but not for participant 2 and 3. For signals from Ext and Fix, it's not suitable for all participants. Additional of classifiers must be taken into account to ensure that this device is suitable for all types of users and there is one real-time assessment method to choose which classifiers that would produce highest accuracy.

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