

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

Mohd Hanafi Muhammad Sidik^{1,*}, Saiful Anwar Che Ghani¹, Abdul Nasir¹, Norain Abdullah²

¹ Faculty of Mechanical and Automotive Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, Pahang, Malaysia

² Bio-Coke Research Institute, Kindai University, Osaka, Japan

ARTICLE INFO	ABSTRACT
<i>Keywords:</i> Electromyography; probability density function; Arduino; instrumented wheelchair; Myoware	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.
Electromyography; probability density function; Arduino; instrumented wheelchair; Myoware	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.

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

* Corresponding author.

E-mail address: hanafisidik@umpsa.edu.my

https://doi.org/10.37934/araset.65.2.1928

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	Average recovery		
					time (s)	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. 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)).

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2} \tag{1}$$

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

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

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

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



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. 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. 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	Contact phase					
		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. 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.

Acknowledgement

The author wishes to express profound gratitude to the Universiti Malaysia Pahang Al-Sultan Abdullah for their invaluable support and financial assistance under the grant RDU Number RDU230328.

References

- [1] Salimi, Zohreh, and Martin William Ferguson-Pell. "Investigating the test-retest reliability of Illinois Agility test for wheelchair users." *PloS One* 15, no. 10 (2020): e0241412. <u>https://doi.org/10.1371/journal.pone.0241412</u>
- [2] Babu, Devin, Abdul Nasir, Mohannad Farag, and Waheb A. Jabbar. "3D printed prosthetic robot arm with grasping detection system for children." *International Journal on Advanced Science, Engineering and Information Technology* 13, no. 1 (2023): 226. <u>http://dx.doi.org/10.18517/ijaseit.13.1.16547</u>
- [3] Civitarese, Gabriele, Sergio Mascetti, Alberto Butifar, and Claudio Bettini. "Automatic detection of urban features from wheelchair users' movements." In 2019 IEEE International Conference on Pervasive Computing and Communications (PerCom), p. 1-10. IEEE, 2019. <u>http://doi.org/10.1109/PERCOM.2019.8767422</u>
- [4] Ab Rahman, Noor Fadzilah, Shir Li Wang, Theam Foo Ng, and Amr S. Ghoneim. "Artificial intelligence in education: A systematic review of machine learning for predicting student performance." *Journal of Advanced Research Applied Science and Engineering Technology* 54, no. 1 (2025): 198-221. http://doi.org/10.37934/araset.54.1.198221
- [5] Sidik, M. M., S. C. Ghani, and Mahfodzah M. Padzi. "Development of a wireless surface electromyography (SEMG) signal acquisition device for power-assisted wheelchair system." *International Journal of Engineering and Advanced Technology* 8, no. 6 (2019): 3414-3418. <u>http://doi.org/10.35940/ijeat.F9511.088619</u>
- [6] Reaz, Mamun Bin Ibne, M. Sazzad Hussain, and Faisal Mohd-Yasin. "Techniques of EMG signal analysis: detection, processing, classification and applications." *Biological Procedures Online* 8 (2006): 11-35. <u>https://doi.org/10.1251/bpo115</u>
- [7] Zhang, Xiaochen, Jiazhen Li, Lingling Jin, Jie Zhao, Qianbo Huang, Ziyang Song, Xinyu Liu, and Ding-Bang Luh. "Design and Evaluation of the extended fbs model based gaze-control power wheelchair for individuals facing manual control challenges." *Sensors* 23, no. 12 (2023): 5571. <u>https://doi.org/10.3390/s23125571</u>
- [8] Esposito, Daniele, Gaetano Dario Gargiulo, Nawadita Parajuli, Giuseppe Cesarelli, Emilio Andreozzi, and Paolo Bifulco. "Measurement of muscle contraction timing for prosthesis control: A comparison between electromyography and force-myography." In 2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA), p. 1-6. IEEE, 2020. <u>http://doi.org/10.1109/MeMeA49120.2020.9137313</u>
- [9] Abdulmalek, Suliman, Abdul Nasir, Waheb A. Jabbar, Mukarram AM Almuhaya, and Devin Babu. "An internet of wearable things (IOWT) based system for smart healthcare monitoring." In *Engineering Technology International Conference (ETIC 2022)* 2022, p. 255-261. IET, 2022. <u>https://doi.org/10.1049/icp.2022.2622</u>
- [10] Awad, Salim Fattah, and Fahad Mohanad Kadhim. "Compare EMG signals by using Myo-Ware muscle sensor and Myo-Trace device for measuring the electrical activity of the muscles." In AIP Conference Proceedings 2386, no. 1. AIP Publishing, 2022. <u>https://doi.org/10.1063/5.0067239</u>
- [11] Shirzadi, Mehdi, Hamid R. Marateb, Kevin C. McGill, and Miquel Angel Mañanas. "Rigorous performance assessment of the algorithms for resolving motor unit action potential superpositions." *Journal of Electromyography and Kinesiology* 56 (2021): 102510. <u>https://doi.org/10.1016/j.jelekin.2020.102510</u>
- [12] Chen, Chen, Shihan Ma, Xinjun Sheng, Dario Farina, and Xiangyang Zhu. "Adaptive real-time identification of motor unit discharges from non-stationary high-density surface electromyographic signals." *IEEE Transactions on Biomedical Engineering* 67, no. 12 (2020): 3501-3509. <u>http://doi.org/10.1109/TBME.2020.2989311</u>
- [13] Navallas, Javier, Adrián Eciolaza, Cristina Mariscal, Armando Malanda, and Javier Rodráguez-Falces. "EMG probability density function: A new way to look at EMG signal filling from single motor unit potential to full interference pattern." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31 (2023): 1188-1198. <u>http://doi.org/10.1109/TNSRE.2023.3241354</u>
- [14] Kusuru, Durgesh, Anish C. Turlapaty, and Mainak Thakur. "A laplacian-gaussian mixture model for surface emg signals from upper limbs." In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), p. 681-685. IEEE, 2021. <u>http://doi.org/10.1109/EMBC46164.2021.9630143</u>
- [15] de Vries, Wiebe HK, Rienk MA van der Slikke, Marit P. van Dijk, and Ursina Arnet. "Real-life wheelchair mobility metrics from IMUs." Sensors 23, no. 16 (2023): 7174. <u>https://doi.org/10.3390/s23167174</u>
- [16] Rammer, Jacob R., Joseph J. Krzak, Brooke A. Slavens, Jack M. Winters, Susan A. Riedel, and Gerald F. Harris. "Considering propulsion pattern in therapeutic outcomes for children who use manual wheelchairs." *Pediatric Physical Therapy* 31, no. 4 (2019): 360-368. <u>http://doi.org/10.1097/PEP.00000000000649</u>
- [17] Huenaerts, C., T. Dewit, D. Soentjens, D. Monari, A. Van Campenhout, and K. Desloovere. "Differences in surface electrode placement and its effect on duration of EMG activity." *Gait & Posture* 97 (2022): S7-S8. <u>https://doi.org/10.1016/j.gaitpost.2022.07.014</u>
- [18] Hermann, Aljoscha, and Veit Senner. "EMG-pants in Sports: Concept Validation of Textile-integrated EMG Measurements." In *icSPORTS*, p. 197-204. 2020. <u>http://doi.org/10.5220/0009982401970204</u>

- [19] Lyons, Nathan R., Matthew TO Worsey, Daniel Devaprakash, Yana A. Salchak, David V. Thiel, Sam Canning, David G. Lloyd, and Claudio Pizzolato. "Washable garment-embedded textile electrodes can measure high quality surface EMG data across a range of motor tasks." *IEEE Sensors Journal* (2023). <u>http://doi.org/10.1109/JSEN.2023.3295773</u>
- [20] Bawa, Anthony, and Konstantinos Banitsas. "Design validation of a low-cost EMG sensor compared to a commercial-based system for measuring muscle activity and fatigue." Sensors 22, no. 15 (2022): 5799. <u>https://doi.org/10.3390/s22155799</u>
- [21] Madansingh, Stefan I., Emma Fortune, Melissa M. Morrow, Kristin D. Zhao, and Beth A. Cloud-Biebl. "Comparing supraspinatus to acromion proximity and kinematics of the shoulder and thorax between manual wheelchair propulsion styles: A pilot study." *Clinical Biomechanics* 74 (2020): 42-50. https://doi.org/10.1016/j.clinbiomech.2020.01.016
- [22] Franchin, Sara Maria, Federico Giordani, Michele Tonellato, Michael Benazzato, Giuseppe Marcolin, Paolo Sacerdoti, Francesco Bettella, Alfredo Musumeci, Nicola Petrone, and Stefano Masiero. "Kinematic bidimensional analysis of the propulsion technique in wheelchair rugby athletes." *European Journal of Translational Myology* 30, no. 1 (2020). http://doi.org/10.4081/ejtm.2019.8902
- [23] Makaram, Navaneethakrishna, Periyamolapalayam Allimuthu Karthick, and Ramakrishnan Swaminathan. "Analysis of dynamics of EMG signal variations in fatiguing contractions of muscles using transition network approach." *IEEE Transactions on Instrumentation and Measurement* 70 (2021): 1-8. http://doi.org/10.1109/TIM.2021.3063777
- [24] Byfield, Richard, Richard Weng, Morgan Miller, Yunchao Xie, Jheng-Wun Su, and Jian Lin. "Realtime classification of hand motions using electromyography collected from minimal electrodes for robotic control." *International Journal of Robotics and Control* 3 (2021): 13. <u>https://doi.org/10.5430/ijrc.v3n1p13</u>
- [25] Botter, Alberto, Taian M. Vieira, Tommaso Geri, and Silvestro Roatta. "The peripheral origin of tap-induced muscle contraction revealed by multi-electrode surface electromyography in human vastus medialis." *Scientific Reports* 10, no. 1 (2020): 2256. <u>https://doi.org/10.1038/s41598-020-59122-z</u>
- [26] Cracchiolo, Marina, Alessandro Panarese, Giacomo Valle, Ivo Strauss, Giuseppe Granata, Riccardo Di Iorio, Thomas Stieglitz, Paolo M. Rossini, Alberto Mazzoni, and Silvestro Micera. "Computational approaches to decode grasping force and velocity level in upper-limb amputee from intraneural peripheral signals." *Journal of Neural Engineering* 18, no. 5 (2021): 055001 1. <u>https://doi.org/10.1088/1741-2552/abef3a</u>