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A REAL-TIME EMG PATTERN RECOGNITION CONTROL METHOD FOR ACTIVATION OF INSTRUMENTED WHEELCHAIR POWER ASSIST SYSTEM

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ABSTRACT

Pattern recognition control method is widely used for surface electromyography (sEMG) application to differentiate movement types according to Motor Unit Action Potential (MUAP). MUAPs detected from muscles are taken as indicators to activate DC motors in assistive equipment such as prosthetic hand and instrumented wheelchair. Performance of control method can be measured through classification accuracy and very important before commercialization. Therefore, the objective of this study is to measure the classification accuracy of pattern recognition control method classifier, which is called Probability Density Function (PDF), in predicting hand movement activities either in contact or recovery phase during wheelchair propulsion. Arduino board was designed to produce a command signal to activate the power-assist system (PAS) when the test subject is propelling the wheelchair forward. The developed method was tested against 5 able-bodied healthy subjects, where sEMG electrodes were placed on namely BIC, TRI, EXT, and FIX muscles. The accuracy results were found to be different for each subject. The highest was 99.4% while the lowest was 48.7%. It was found that low classification accuracy is due to PAS was activated in the recovery phase where it is supposed to remain in off condition. Consequently, PDF control method is effective for subject number 1 only where the hand movements have been successfully identified based on MUAP.

1. Introduction

Healthcare and engineering are two fields that benefited from the advancement of electromyogram (EMG) which has the ability to recognize limb motions [1]. For instance, intensive therapy activities that involve recognizing a patient's movement intention bring a positive effect on the rehabilitation process for stroke patients [2]. Furthermore, by recognizing the intention, a human can control rehabilitation such as a prosthetic leg and instrumented wheelchair with neuromuscular-mechanical fusion-based interface device [3-5]. In fact, EMG pattern recognition systems have been widely used as an interface in various type of applications in man-machine such as an instrumented wheelchair, prosthetic hand and leg, virtual mouse, and keyboard [6]. These kinds of man-machine are extracting surface EMG (sEMG) signals where electrodes are placed on the skin above the targeted muscle.

But, sEMG signals always mixed from several muscles located near to the electrode and contain noise that causes limb motion recognition to become difficult [7]. Feature plays an important role in the EMG recognition system. The simplest features are time-domain features such as root mean square (RMS) and mean absolute value (MAV) that widely used because of computational simplicity [8].

Implementation of these features showing improvement in classification accuracy for the control system of developed man-machines [9, 10]. Many studies have been conducted and the obtained result of classification accuracy were above 90% in real-time applications [11]. However, translation into the real application by connecting to the actuator is very limited [12]. Classification accuracy of EMG pattern recognition is depending on many factors such as electrode shifting and varying force during muscular contraction becoming challenges for long term EMG control systems [13, 14].

Researches on instrumented wheelchair control system are mostly focusing on the user interface to control the power assist system based on limb motion [15]. A conventional electric wheelchair is using a joystick to control movement direction. But, there are limitations on joystick control for a disabled person that has a lack of full dexterous control of their arm [16].

Meanwhile, for a manual wheelchair, these person has no ability to propel the push rim due to low in muscles strength [17]. An instrumented wheelchair is not just assisting the user in maneuvering around, but at the same time can be a piece of rehabilitation equipment to help them restoring back to their normal life by improving the muscle strength.

There are two types of rehabilitation exercise which are active and passive. Active type is proven better compared to passive exercise in improving muscle strength [18, 19]. For example, propelling a manual wheelchair is a good exercise in increasing the strength of arm muscles.

However, a disabled person has a limitation in producing enough force to propel it. This is where a power-assisted system (PAS) can provide assistance by reducing the propulsion force. In this study, an assisting system to integrate between power assist and sEMG data acquisition device was developed for an instrumented wheelchair. The system is functioning by recognizing arm motion during wheelchair propulsion using a real-time pattern recognition control method.

2. Methodology

A. Subjects

5 able-bodied and healthy male subjects were volunteered to participate in this study. All of them are students of Universiti Kuala Lumpur Malaysia France Institute and their details are tabulated in Table 1. The mean age is 22 ± 1 years, height 162 ± 8 cm, and a weight of 60 ± 10 kg. Participants have no previous experience with EMG interface control wheelchair.

A briefing session conducted to explain about hand movement pattern and timeline for the experiment. 12 minutes of training time is given for subjects to get used to the propulsion method. All of them were given a consent letter to participate in this study as per instructed by the university's research ethics committee.

TABLE I. *Subject Details*

Subject (Gender)	Age (year)	Heigh t (cm)	Weight (kg)	Contact time (s)	Recovery time (s)
1	20	156	49	1.63	1.76
2	24	171	56	2.12	1.33
3	22	172	78	1.13	1.89
4	21	154	55	1.11	1.61
5	21	158	61	1.16	1.01

B. Data Acquisition

4 Myoware muscle sensors that consist of 16 surface electrodes connected to Arduino MEGA 2560 microcontroller board was used to record the Motor Unit Action Potential (MUAP). Silver-Silver Chloride (Ag-AgCl) surface electrode used in this study. Ag-AgCl electrode is a gelled electrode as a chemical (AgCl) interface between skin and metallic (Ag) part of electrode for the current to move freely between electrolyte and electrode [20].

Sensors were placed on arm to record MUAP during propelling a wheelchair. Arm skin was shaved and cleaned with alcohol before surface electrodes are placed to reduce noise between the electrode and the skin. The location of sensors placement on targeted muscles is referred to Non-Invasive Assessment of Muscles (SENIAM) guidelines.

4 muscles were selected to be placed surface electrodes which are Biceps Brachii (BIC), Triceps Brachii (TRI), Extensor Digitorum (EXT), and Flexor Digitorum (FIX). Arduino MEGA 2560 connected using a USB cable to a laptop to store MUAP value for further analysis purposes. The flow of sEMG signal from sensing MUAP in muscles to activation of PAS as in Figure 1.

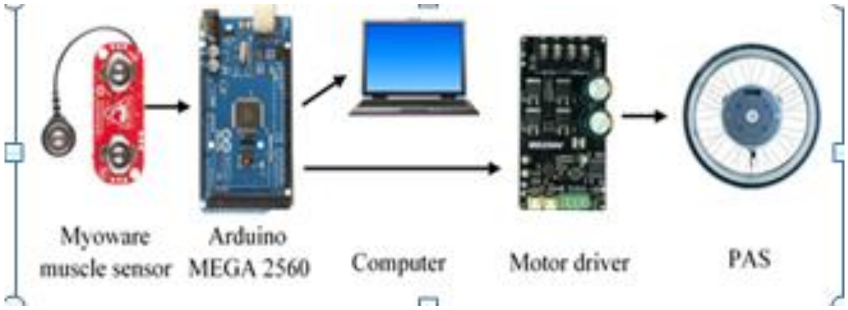

Figure 1. *Flow of sEMG signal*

C. Experiment Protocol

Subjects are instructed to sit on the wheelchair and their right arm is cleaned and shaved to place the surface electrodes. During wheelchair propulsion, hand activity can be divided into 2 phases - contact and recovery. The contact phase is when the subject is gripping the wheelchair's push rim and propel forward that would cause the wheelchair to move forward. Hand position moved from position A to B as in Figure 2. Meanwhile, for the recovery phase, the subject's hand returns to the starting position in the contact phase (B to A) and the wheelchair is not moving in this phase. The hand movement pattern during both phases is an arc. Arc pattern requires the subject's hands to touch the push rim all the time. Other patterns are single loop, double loop, and semicircular, as shown in Figure 2. The experiments were conducted on a tiled floor.

Duration of experiment 110 s involving 3 stages - individual data collection, calculation period, and method selection, as shown in Figure 3. Individual data collection is between 0 to 50 s, where pattern recognition control method was trained based on the separated phase between 5 contact phases and 5 recovery phases. This is where subjects have to propel forward 5 times and do hand return activity alternately. Between 50 to 60 s, calculations of MUAP mean and standard deviation (SD) in the previous stage are done and no wheelchair propulsion activity during this time. Validation of control method is between 60 to 110s and involving the same method as on the individual data collection stage.

Probability Density Function (PDF) is the pattern recognition classifier used in this study. PDF was proven to has a high classification accuracy and good in handling for sEMG application [21, 22]. The equation of PDF is given in Figure 4. PDF is comparing the probability between values from the contact and recovery phase to discern which one has higher value using 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.

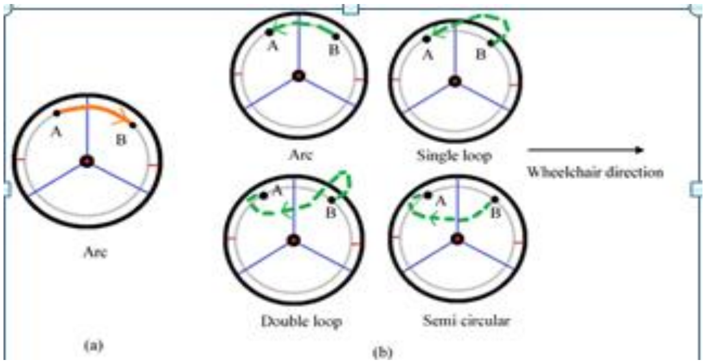

Figure 2. *Hand movement pattern: (a) contact phase, (b) recovery phase*

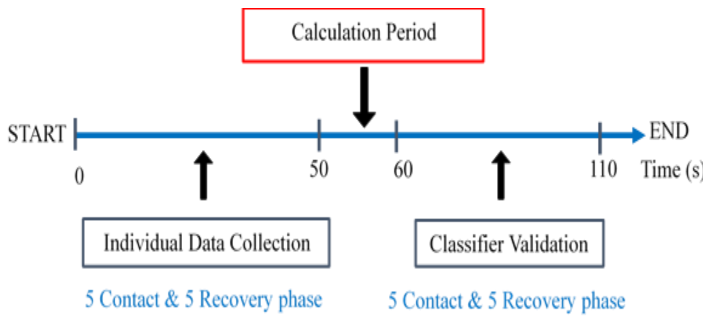

Figure 3. *Stages of experiment*

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

e = 2.71828
π = 3.14159
μ = Mean
σ = Standard deviation
X = sEMG value

Figure 4. *PDF equation*

D. Double threshold control method and transverse channel

Activation of power-assist system depending on one single muscle or called as single threshold would produce a higher rate of error in recognizing the MUAP pattern [23]. This matter can be overcome by implementing a double threshold control method. The double threshold is by adding another muscle as the indicator for PDF to recognize the MUAP pattern to differentiate hand movement in contact and recovery phases. The selection of pair muscles is based on a transverse channel by combining sEMG signals from two opposing muscles such as BIC pairing with TRI and EXT paired with FIX.

3. Experimental Results

Figure 5 shows MUAP for subject 1 for the whole experiment. The total experiment duration is 110 s, which were divided into 3 stages (individual data collection, calculation period, and classifier validation). The maximum value of MUAP in each phase was determined. Table 2 shows the mean and SD of MUAP for all subjects collected during individual data collection experiments. The highest mean for subject 1 is 3.02 V for EXT muscle and the highest SD is

±1.60 V for TRI. For subject 2, the highest mean is 4.69 V (FIX) and the highest SD is ±0.77 V (EXT). For subject 3, the highest mean is 4.74 V (FIX) and the highest SD is ±1.38 V (TRI). For subject 4, the highest mean and SD which belong to FIX are 3.83 V and ±0.74 V, respectively. Similarly, for subject 5 where FIX has the highest mean and SD, which are1.33 V and ±0.37 V, respectively. Figure 6 is placement of sEMG sensors onto targeted muscles.
Figure 7 shows the performance of the PDF control method in differentiating MUAP patterns in contact and recovery phases for subject 1 with results from BIC & TRI muscles. PAS switched on when Arduino board sending signal “1” to the motor driver that acts as an interface between the processor and DC motor by allowing higher current and voltage based on a low-current control signal. Meanwhile, when the signal is “0”, PAS is in off condition. PAS was switched on in contact phase 7, 8, and 9 only. It remains in off condition for all recovery phases and contact phase 6 and 10. In contact phase 7, PAS switched on for 0.58 s, 0.12 s for contact phase 8, and 0.63 s in contact phase 9. Figure 8 shows the performance of PDF for subject 1 with results from EXT & FIX muscles. PAS was switched on in contact phase 6 and 7, and recovery phase 9. In contact phase 6, PAS switched on for 0.75s, 0.53s for contact phase 7 and 0.21s in recovery phase 9. Compared with the combination of BIC & TRI, PAS switched on during the recovery phase where it should remain in off condition.
Classification accuracy determined for all subjects is given in Table 3. The highest accuracy is 99.4% for subject 2 from BIC & TRI muscles and the lowest is 48.7% for subject 5 from BIC & TRI muscles. Average classification accuracy for EXT & FIX is 94.6%, which is higher than BIC & TRI (48.7%).

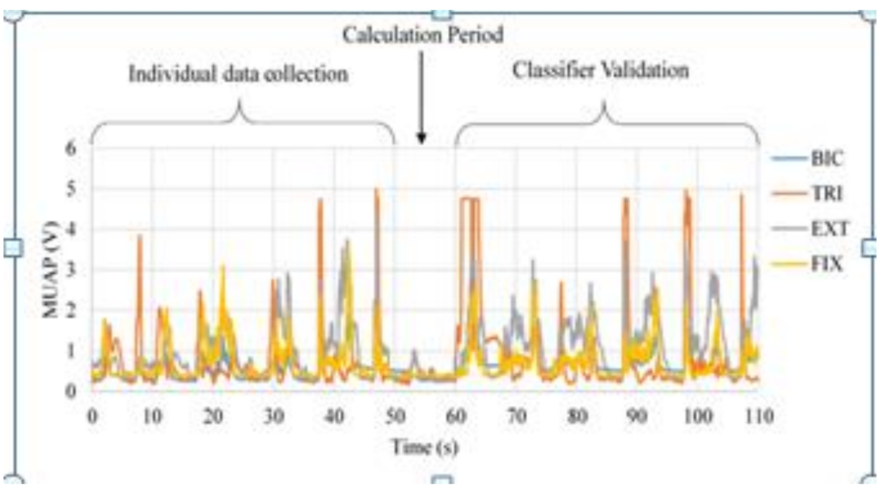

Figure 5. *Experiment MUAP result for subject 1*

TABLE II. *Mean and sd for all subjects. C is contact phase and r is recovery phase*

Phase		Mean ± SD (V)				
		Subject 1	Subject 2	Subject 3	Subject 4	Subject 5
BIC	C	1.52 ± 0.32	3.74 ± 0.12	3.42 ± 0.15	1.26 ± 0.25	0.87 ± 0.26
	R	1.36 ± 0.44	2.24 ± 0.86	2.87 ± 0.87	1.06 ± 0.14	0.78 ± 0.06
TRI	C	1.95 ± 1.60	2.78 ± 0.16	4.02 ± 1.38	1.49 ± 0.36	0.69 ± 0.34
	R	3.71 ± 1.59	2.52 ± 1.29	3.09 ± 1.80	1.14 ± 0.24	0.54 ± 0.10
EXT	C	3.02 ± 0.26	4.08 ± 0.77	4.24 ± 1.27	1.19 ± 0.33	0.58 ± 0.15
	R	2.96 ± 0.77	4.69 ± 0.01	3.73 ± 1.47	1.06 ± 0.59	0.67 ± 0.23
FIX	C	2.36 ± 0.30	4.69 ± 0.03	4.74 ± 0.01	3.83 ± 0.74	1.33 ± 0.37
	R	1.41 ± 0.43	1.88 ± 1.97	3.70 ± 1.48	3.78 ± 0.79	1.49 ± 0.28

Figure 6. *Placement of 4 Myoware muscle sensors on BIC, TRI, EXT and FIX muscles*

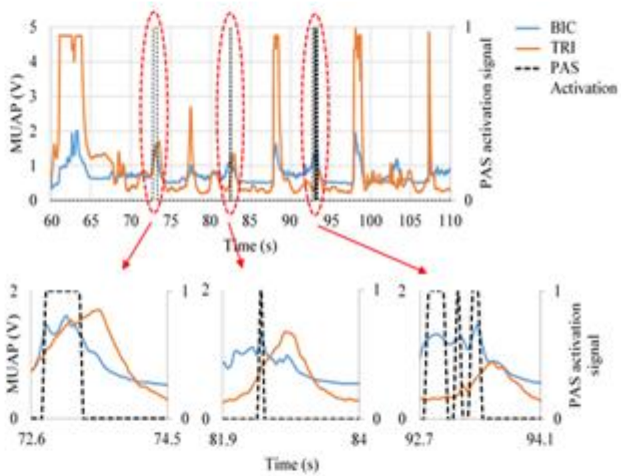

Fig. 7. *PDF control method performance for subject 1 based on BIC & TRI MUAP signals*

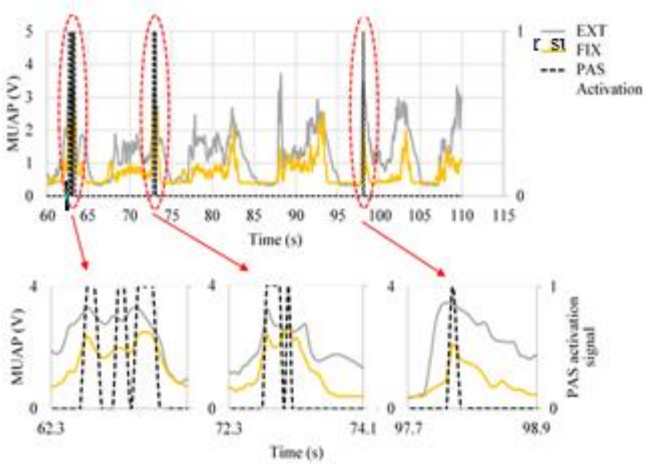

Fig. 8. *PDF control method performance for subject 1 based on EXT & FIX MUAP signals*

TABLE III. *CLASSIFICATION ACCURACY*

Muscle	Subject				
	1	2	3	4	5
BIC & TRI	95.8 %	99.4 %	94.5 %	78.1 %	48.7 %
EXT & FIX	95.2 %	95.8 %	94.5 %	94.6 %	92.7 %

4. DISCUSSION

PDF pattern recognition control method has been successfully tested on 5 subjects to differentiate MUAP patterns during wheelchair propulsion. The mean MUAP value for the contact phase is normally higher than the recovery phase due to the amount of force required is different in both phases. However, some subjects have mean MUAP in the recovery phase higher than the contact phase. For example, EXT muscle for subject 2 has a higher mean MUAP in the recovery phase (4.69 V) compared to 4.08 V in the contact phase. This kind of result would affect the classification accuracy. But for subject 2 (EXT) case, he has higher MUAP value in all recovery phases compare to the contact phase during data collection experiment as in Table 4.

TABLE IV. *Subject 2 Ext Muap Result For Contact And Recovery Phases*

Muscle	Phase	MUAP (V)				
		Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
EXT	Contact	4.65	3.57	2.95	4.60	4.60
	Recovery	4.70	4.69	4.70	4.69	4.67

TABLE V. *Subject 5 Muap Result For Bic And Tri Muscles*

Muscle	Phase	MUAP (V)				
		Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
BIC	Contact	1.33	0.80	0.81	0.69	0.71
	Recovery	0.81	0.85	0.78	0.70	0.73
TRI	Contact	1.30	0.59	0.52	0.58	0.46
	Recovery	0.59	0.69	0.54	0.46	0.43

For the lowest classification accuracy, which is 48.7%, has been recorded for subject 5. The trend for BIC is different as contact phase 1 and 3 is higher than recovery phase 1 and 3 as in Table 5. However, in other phases, the values are opposite. Meanwhile, for TRI, contact phase 1, 4 and 5 are higher than the recovery phase. This kind of pattern is difficult for PDF control method to differentiate the movement based on phase only.PAS activation is depending on MUAP pattern based on training data for both phases. PAS must be switched on in contact phase only, where subjects are propelling forward to move the wheelchair.
PAS can’t be activated during the recovery phase because during this is moment, the subject’s hands are moving back to get ready for the next contact phase. Activation PAS at a wrong timing will harm the wheelchair user by moving forward that is not tally with user desire. As for subject 1, signals from BIC & TRI indicated PAS to power on in 3 out of contact phase and none in recovery phases. Meanwhile, for EXT & FIX, PAS switched on 2 times out of 5 contact phases and once in the recovery phase. Such a thing must be avoided and a condition should be added into the coding to stop the PAS from switching on during the recovery phase. Figure 9 shows PAS activation during the contact and recovery phase for all subjects.

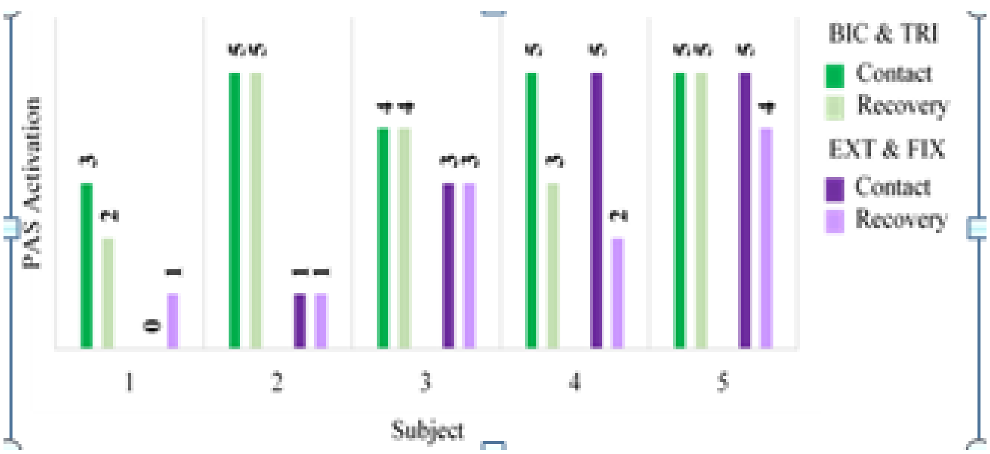

Figure 9. *PAS activation times for all subjects in contact and recovery phases*

5. Conclusion

A real-time EMG pattern recognition using a PDF control method classifier has been conducted experimentally to activate the Power Assist System (PAS) of an instrumented wheelchair. Based on the signals acquired from the hand muscles, the developed system successfully classified the movement of the subject's hand with accuracy between 48.7% to 99.4%. Regardless of the results, the developed system showed potential in translating the muscle's signal to activate PAS, which is very beneficial in the rehabilitation process. In the future, the use of artificial intelligence combined with a high-speed microcontroller is expected to significantly improve the developed system.

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