Comparison of Five Time Series EMG Features Extractions Using Myo Armband

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***Abstract*—Feature extraction is meant to get representation and information that embedded in the signals, this is necessary to minimize complexity of implementation and reduce the cost of information processing. Recently, there are many methods for features extraction. This research is comparing five feature extractions from eight channels electromyography (EMG) signals that obtained from Myo Armband located on forearm muscles in order to get significant differences when hand do some movements. The time series features extraction that evaluated are Mean Absolute Value (MAV), Variance (VAR), Willison Amplitude (WAMP), Waveform Length (WL), and Zero Crossing (ZC). The variety of hand movement are fist, rest, half-fist, gun-point, and mid-finger fold. Moreover, the result shows that the rank of evaluated features extraction always showhs same results in four experiment, MAV is always giving the best performance WL. From this finding, MAV and WL are two recommendation for time series features extraction. This rank of time series features extraction gives worthiness when process information in future development research.**

***Index Terms*—features extraction; electromyography; myo armband.**

I. INTRODUCTION

Hand is one of the most important organ for human activity because it has main role to process something like taking, grabbing, touching, or lifting. Classification and identification Electromyography (EMG) signals are challenging in several area especially in forearm because due to hand's gesture movement and activity [1]. Time series features extraction are methods to extract informations that embedded in EMG signals in sequence data points over time interval. In this research, there are five evaluated different features extraction that widely used to classify EMG, Mean Absolute Value (MAV), Variance (VAR), Willison Amplitude (WAMP), Waveform Length (WL), and Zero Crossing (ZC) [2][3]. Han-Pang Yuan et al [3] perform off-line experimental use three channel EMG in several muscles and report that integral of EMG (in this case called MAV) is the third rank under histogram of EMG (HEMG) and autoregressive model (ARM). HEMG is the extension of WL and ZC and ARM that use is fourth-order autoregressive Gaussian stationary process. After that WL, VAR, and ZC followed in the 4th, 5th, and 7th rank. Another application based on traditional EMG are Qiang Li et al. [4] perform four channels surface EMG in several muscles and use three features extraction, MAV, VAR, and AR. Hsiu-Jen Liu and Kuu Young Young [5] perform four features extraction MAV, VAR, ZC, and WAMP in upper-arm to classify the movements.

Obtaining EMG signals from traditional surface electrodes has advantages in selecting muscles that moves the hand. Features extraction from this EMG signals already has significant differences in each channel that generate the signals. But nowadays, application that use traditional surface electrodes is less popular. This research use Myo armband that consist of eight channels electrodes and sends the EMG signals trough wireless connection. So the application based on Myo armband is more compact and has better appearance. But Myo's electrodes cannot select proper muscles in forearm. Beside that Myo armband already has five default gestures to perform, they are fist, rest, wave-in, wave-out, and click.

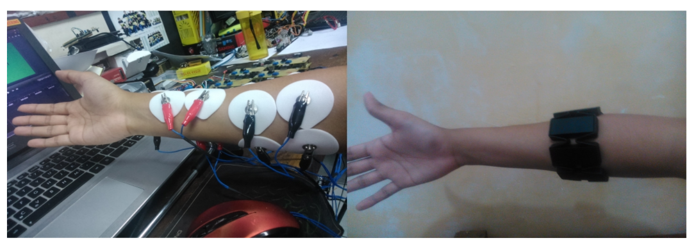


Fig. 1: Traditional surface electrodes vs Myo armband

Electrodes in Myo armband is circular positions and the main muscles that covered are Extensor Digitorum and Flexor Digitorum. These are the muscles that move wrist, index, middle, ring, and little finger. The gestures in this research are focusing into fingers movement only. This gestures are more difficult than default Myo's gestures that focus on wrist movement. And then evalute five features extraction using statistical student t-test.

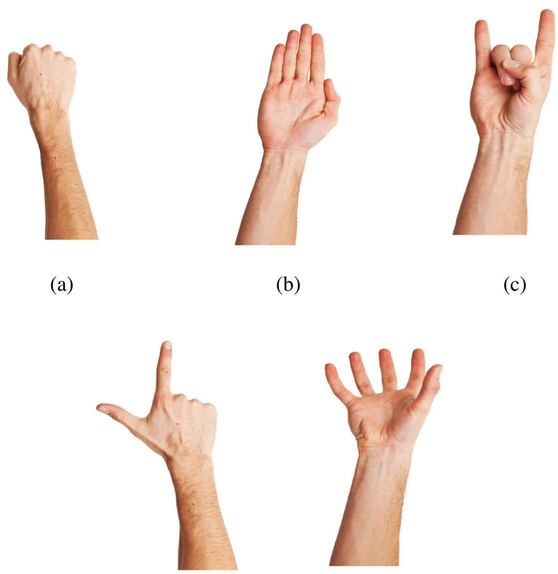
The idea to evaluate features extraction is comparing p-value that generated from t-test. The p-value is summed as Total Point (TP). The lower TP gives better performance and higher TP gives less performance.

II. MATERIAL AND METHODS

A. EMG signals measurement and gestures

In Myo armband, the EMG data from eight channels has range from -127 to 127 in ADC units. This is not necessary to convert into voltage because the actual EMG units in voltage is extremely small in microvolt range.

Unlike default Myo's gestures, the gestures in this experiment will perform more fingers movement, they are fist (F), rest (R), half-fist (HF), gun-point (GP), and mid-finger fold (MF) as follows in Figure 2.



(a) (b) (c)

(d) (e)

Fig. 2: Five types of gestures (a) fist, (b) rest, (c) mid-finger fold, (d) gun-point, and (e) half-fist.

The data from these movements is send to PC trough Bluetooth Low Energy (BLE) wireless connection. The Myo armband electrodes configurations setting is like Figure 3.a, fourth channel (CH4) that has blue marker is in lower forearm followed by third channel (CH3) in clockwise and fifth channel (CH5) in counter clockwise.

(a)

(b)

Fig. 3: Eight channels Myo armband EMG signals (a) channel assigment (b) examples of EMG data.

B. Time series features extraction candidate

The five kinds of time series features extraction that will be evaluated in this research as follows:

• Mean Absolute Value (MAV)

MAV is estimate of summation absolute value and measure contraction level of the EMG signals [3] the other name, MAV is an integral of EMG. It is given by:

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|X_k| \tag{1}$$

Where X_k is EMG data at k and N is number of samples.

• Variance (VAR)

VAR is measure density power of EMG signals [3]. It is given by:

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N}X_k^2 \tag{2}$$

• Willison Amplitude (WAMP)

WAMP count for each change of the EMG signals amplitude that exceeds a defined threshold. It is given by:

$$WAMP = \sum_{k=1}^{N} f(|X_k - X_{k+1}|) \tag{3}$$

Where:

$$f(x) = \begin{cases} 1 & x > threshold \\ 0 & otherwise \end{cases}$$

• Waveform Length (WL)

WL is cumulative variation that can indicate the degree variations of EMG signals. It is given by:

$$WL = \sum_{k=1}^{N}|X_{k+1} - X_k| \tag{4}$$

• Zero Crossing (ZC)

ZC count the number of times that signals cross zero line. A threshold needed to reduce the noise in zero crossing in this case has value 0.4. ZC is calculated as:

$$ZC = \sum_{k=1}^{N} sgn([X_k - 0.4][X_{k+1} - 0.4]) \tag{5}$$

Where:

$$sgn(x) = \begin{cases} 1 & x > threshold \\ 0 & otherwise \end{cases}$$

C. Statistical Analysis

The differences that given by features extractions to determine the gestures are evaluated using two samples student T-Test with default significance level $\alpha = 0.05$ or $\alpha = 5\%$.

$$t = \frac{\overline{x_s} - \overline{y_s}}{\sqrt{\frac{\sum(x_i - \overline{x_s})^2 + \sum(y_i - \overline{y_s})^2}{N_x + N_y - 2}\left(\frac{1}{N_x} + \frac{1}{N_y}\right)}} \tag{6}$$

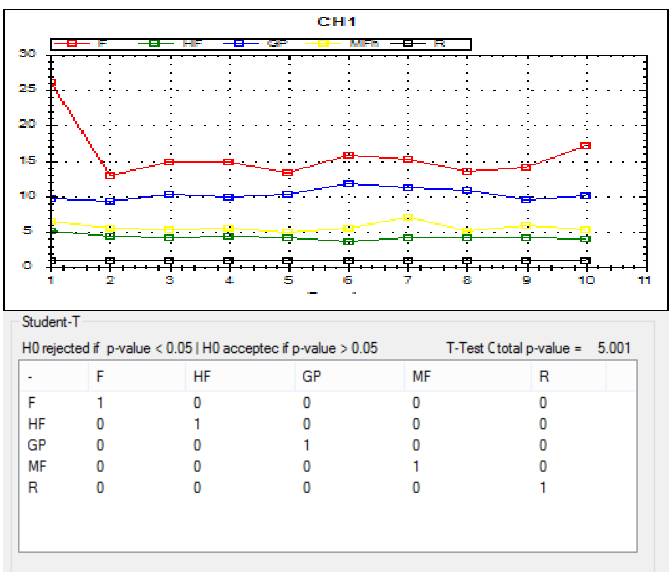
Where x and y are sample means and N is number of samples.

In this research use ALGLIB numerical analysis library that provide statistical hypothesis of two sample T-Test and generate p-value. The p-value (two-tail value) from this T-Test has minimum value 0 and maximum value is 1. It means that the null hypothesis (H0) is rejected when p-value is less than 0.05 or alternative hypothesis (Ha) is accepted. The alternative hypothesis (Ha) is “the signals that are compared is significantly different” and the null hypothesis (H0) is “the signals that are compared is not significantly different”.

III. EXPERIMENTAL RESULT

The subject is asked to performs ten times five different gestures and then sends each EMG data to PC. This EMG data will be extracted and generates five features extraction. The gestures is compared with another gestures pattern to evaluate and get the significant differences. In this research performs four experiment with same subject, from one experiment will generates 8x5=40 data.

This Figure 4 is the result from first channel (CH1) for MAV and student t-test.

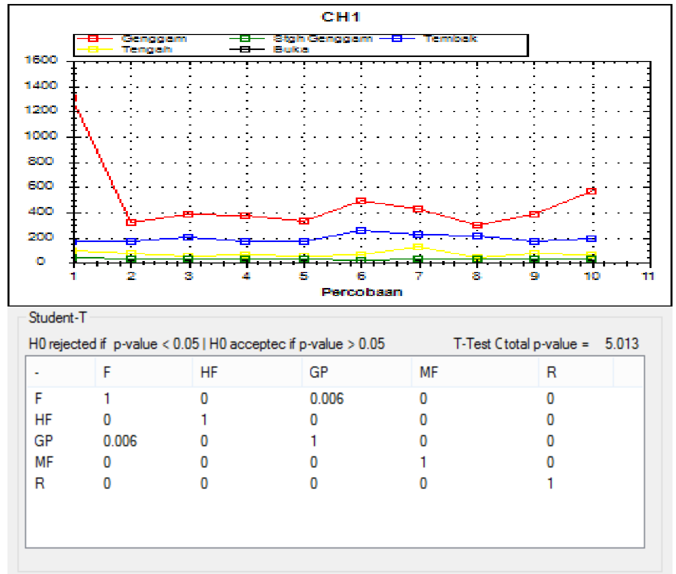


-	F	HF	GP	MF	R
F	1	0	0	0	0
HF	0	1	0	0	0
GP	0	0	1	0	0
MF	0	0	0	1	0
R	0	0	0	0	1

Fig. 4: MAV pattern and student test from CH1.

F is compared with F or HF is compared with HF itself has p-value=1, it means that these are almost same. F compared to HF has p-value=0, it means that H0 rejected and this signals is significantly different. In simple way to understand is when p-value is less than 0.5 the signals that compared is significantly different. From Figure 4 above that MAV can make significant differences in each gestures, proved by p-value is always rejecting null hypothesis or accepting alternative hypothesis. Total p-value is summation of all p-value that generated from comparing the gestures. One channel will has total p-value range 5 at minimum to 25 at maximum.

This Figure 5 is the result from first channel (CH1) for VAR and student t-test.



-	F	HF	GP	MF	R
F	1	0	0.006	0	0
HF	0	1	0	0	0
GP	0.006	0	1	0	0
MF	0	0	0	1	0
R	0	0	0	0	1

Fig. 5: VAR pattern and student test from CH1.

F is compared to GP or vice versa GP is compared to F has p-value=0.006, it means that significantly different. From Figure 5 show that VAR is giving different significant too. This analysis is applied to another features extraction (WAMP, WL, and ZC) in another channel (CH1 to CH8). The idea to determine that feature extraction is giving best performance and evaluated it, is using total points (TP). TP is summation of total p-value that generated after applies analysis before.

$$TP_{(fe)} = \sum_{i=i}^{8} total\, p\, value_{(fe\, CHi)} \tag{7}$$

The lower TP means that feature extraction is giving best performance and will be the higher rank. Otherwise, the higher TP means that feature extraction is giving less performance and will has lower rank. Table 1 below is result from first experiment, consists of total p-value and the TP.

TABLE I: First Experiment

Channel	Features				
	MAV	VAR	WAMP	WL	ZC
CH1	5.001	5.013	6.088	5.001	6.827
CH2	5.000	5.004	6.180	5.001	8.522
CH3	6.386	7.240	8.228	6.300	8.458
CH4	5.950	6.234	8.162	6.366	14.348
CH5	5.667	6.120	5.197	5.867	6.798
CH6	5.652	7.277	7.874	5.448	6.276
CH7	5.103	5.134	5.690	5.095	6.069
CH8	5.633	5.928	7.432	5.475	5.328
TP	44.392	47.950	54.851	44.553	62.626
Rank	1	3	4	2	5

From first experiment show that MAV has the first rank because has lower TP (44.392), followed by WL (44.553), VAR (47.950), WAMP (54.851), and ZC (62.626).

TABLE II: Second Experiment

Channel	Features				
	MAV	VAR	WAMP	WL	ZC
CH1	5.000	5.019	5.102	5.000	5.231
CH2	5.046	5.116	6.471	5.087	8.365
CH3	5.005	5.008	8.488	5.016	9.896
CH4	5.302	5.390	8.921	5.254	6.403
CH5	5.004	5.027	5.174	5.005	6.160
CH6	5.668	5.958	5.881	5.812	5.074
CH7	5.003	5.042	5.340	5.002	5.271
CH8	5.005	5.025	5.125	5.001	6.354
TP	41.033	41.585	50.502	41.177	52.754
Rank	1	3	4	2	5

From second experiment show that MAV has the first rank again (41.033), followed by WL (41.177), VAR (41.585), WAMP (50.502), and ZC (52.754). But the all the TP value is lower than the first experiment.

TABLE III: Third Experiment

Channel	Features				
	MAV	VAR	WAMP	WL	ZC
CH1	5.000	5.002	5.114	5.000	6.761
CH2	5.001	5.006	5.229	5.000	6.156
CH3	6.570	6.328	10.397	6.659	11.097
CH4	5.443	5.584	6.203	5.080	11.330
CH5	6.377	7.014	6.270	6.547	6.458
CH6	5.325	6.331	5.953	5.271	5.427
CH7	6.326	6.978	5.394	6.634	6.576
CH8	5.372	5.358	5.484	5.441	8.367
TP	45.414	47.601	50.044	45.632	62.1722
Rank	1	3	4	2	5

Third experiment is almost same with another two experiment before. MAV has the first rank again (45.414), followed by WL (45.632), VAR (47.601), WAMP (50.044), and ZC (62.172).

TABLE IV: Fourth Experiment

Channel	Features				
	MAV	VAR	WAMP	WL	ZC
CH1	5.213	6.606	5.440	5.015	5.591
CH2	5.203	5.172	5.403	5.424	6.448
CH3	6.421	6.810	9.588	6.931	10.847
CH4	5.160	5.522	10.828	5.241	11.976
CH5	5.428	5.623	9.246	5.700	9.637
CH6	5.711	5.688	8.864	5.723	7.952
CH7	5.000	5.002	5.022	5.000	5.011
CH8	5.000	5.000	5.002	5.241	5.399
TP	43.136	45.423	59.393	44.275	62.861
Rank	1	3	4	2	5

From fourth experiment show that MAV (43.136) has the first rank again, followed by WL (44.275), VAR (45.423), WAMP (59.393), and ZC (62.861). From all four experiment show that MAV is always give the best performance than another features because MAV is always has lower TP. The second best is WL has TP not far enough from MAV's TP. Noticeable one, ZC is giving less recommendation because the TP is always high and has the lower rank.

IV. CONCLUSION

In conclusion, from five features extraction that evaluated, the recommendation for time series feature extraction for EMG signal is Mean Absolute Value (MAV) followed by Waveform Length (WL). The finding in this research will be used in EMG pattern recognition. In future studies, more time series features extraction should be evaluated, make comparison between time series with frequency series and wavelet series, and add recognition system or classifier such as SVM, K-NN, ANN, QDA, and etc.

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