Bulletin of Electrical Engineering and Informatics
Vol. 8, No. 2, June 2019, pp. 533~540
ISSN: 2302-9285, DOI: 10.11591/eei.v8i2.1415

Hand motion pattern recognition analysis of forearm muscle using MMG signals

M. R. Mohamad Ismail[1], C. K. Lam[2], K. Sundaraj[3], M. H. F. Rahiman[4]
[1,2,4]School of Mechatronic Engineering, Universiti Malaysia Perlis, Kampus Pauh Putra, 02600 Arau, Perlis, Malaysia
[3]Faculty of Electronic and Computer Engineering, Universiti Teknikal Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

Article Info

Article history:

Received Dec 1, 2018
Revised Jan 19, 2019
Accepted Feb 26, 2019

Keywords:

Classification
Forearm muscle
Linear discriminant analysis
Mechanomyography

ABSTRACT

Surface Mechanomyography (MMG) is the recording of mechanical activity of muscle tissue. MMG measures the mechanical signal (vibration of muscle) that generated from the muscles during contraction or relaxation action. It is widely used in various fields such as medical diagnosis, rehabilitation purpose and engineering applications. The main purpose of this research is to identify the hand gesture movement via VMG sensor (TSD250A) and classify them using Linear Discriminant Analysis (LDA). There are four channels MMG signal placed into adjacent muscles which PL-FCU and ED-ECU. The features used to feed the classifier to determine accuracy are mean absolute value, standard deviation, variance and root mean square. Most of subjects gave similar range of MMG signal of extraction values because of the adjacent muscle. The average accuracy of LDA is approximately 87.50% for the eight subjects. The finding of the result shows, MMG signal of adjacent muscle can affect the classification accuracy of the classifier.

Corresponding Author:

M. R. Mohamad Ismail,
School of Mechatronic Engineering,
Universiti Malaysia Perlis,
Kampus Pauh Putra, 02600 Arau, Perlis, Malaysia.
Email: razifmohamad144@gmail.com

1. INTRODUCTION

Human consists of many muscles interact each other to perform various activities in daily life. When muscles of the body contracted and relaxed continually, the force produced by muscles based on two mechanisms: the firing frequency and the recruitment of the motor units (MU) [1, 2]. Increasing either the firing frequency or the number of recruited MUs contributes to increasing the muscle force [3]. Contraction of muscle generates signal for many application. The investigation of forearm and finger movement contributes opportunity for many application such as prosthetic control and rehabilitation system [4, 5]. Forearm consist of many muscles interact each other when performing activities such as load lifting, workout etc.

Mechanomyography (MMG) are non-invasive tools that have been used to study muscle activity [6, 7]. MMG is a technique for recording and interpreting mechanical activity (vibration) in contracting muscle [8] at the surface of skins. The signal generated by the low frequency lateral oscillations of active skeletal muscle fibers. According to researchers [9-11], it can be concluded that the frequency range of the signal is normally measured between 3Hz to 100Hz bandwidth. MMG signal can be detected by several types of transducers located on the surface of the skin. According to the literatures, most preferred sensors used for MMG signal are accelerometer [12-15], microphone [16-19], piezoelectric contact sensor [20, 21], laser distance sensor [22, 23].

Linear Discriminant Analysis (LDA) is a well-known classifier used in statistics, pattern recognition analysis and machine learning. LDA is widely used in applications such as speech recognition, muscle activity recognition, etc. It is a method to find a linear combination of features that characterizes or separates two or more classes of objects or events. LDA is easily executed, much faster to train and well-understood representatives of statistical classifiers.

Xie et al. [9] investigated and classified the hand motion using MMG signals for multifunctional prosthetic control. Hand motions performed lead to the noise problem. Therefore, researchers proposed a new scheme to extract robust MMG features by the integration of the wavelet packet transform (WPT), singular value decomposition (SVD) and a feature selection technique based on distance evaluation criteria for the classification of hand motions. The authors illustrated the classification performance (LDA) by compared the method with three other time–frequency decomposition which is short-time Fourier transform (STFT), stationary wavelet transform (SWT) and S-transform (ST). The present result gave the highest average classification accuracy up to 89.7%. The performance of the proposed method for MMG classification was evaluated in the context of a LDA classifier.

Alves and Chau conducted so many researches' using LDA as a classifier. The article [24] was studied to examine if multisite MMG signals exhibit distinctive patterns of forearm muscle activity. There are six forearm muscles: Pronator Teres (PT); Flexor Carpi Radialis and Palmaris Longus (FCR/PL); Flexor Carpi Ulnaris (FCU); Extensor Digitorum Communis (EDC); Extensor Carpi Radialis Longus (ECR); and Extensor Carpi Ulnaris (ECU) were located with accelerometer sensors to collect MMG signals. MMG patterns are specified with 7±1 hand movements of accuracy with 90±4%. 14 features were selected by genetic algorithm before classified using LDA. Other than that, same authors investigated the discriminability of multiple hand motions using multichannel forearm MMG [25]. Six MMG sensors were manufactured according to the method of [26], were placed to the dominant forearm over extrinsic hand muscles. Same forearm muscles were used in previous research [24] with 15 features selected by a genetic algorithm and classified by LDA. MMG signals from six sites was differentiated corresponding to eight hand motions (hand open, hand close, wrist flexion, wrist extension, pronation, supination, adduction, and abduction) of forearm muscle activity with a mean accuracy of 93±9%.

On the other hand, Alves et al. [13] studied the effect of accelerometer location on the classification of single-site forearm mechanomyograms. MMG signal is collected from FCR muscle with three classes of muscle activity: wrist flexion, wrist extension and semi-pronation. Same experiment protocols were conducted compute the average classification accuracy with 91±3% (3 classes, continuous classification). Again, [27] determined whether MMG signal features retained enough discriminatory information allowed reliable continuous classification and determined whether there is a decline in classification accuracy over short time periods. Two accelerometers were placed to the FCR and ECR muscles performed three classes of forearm muscle activity. The average classification accuracy of LDA was 89±2%. The present result indicates, MMG signals recorded at the forearm retained enough discriminatory information to allow continuous recognition of hand motion.

2. METHODOLOGY

2.1. DAQ system

The MP160 System is upgraded data acquisition system, which equipped with hardware and software for the acquisition and various analysis for the signal recorded. It was made with an internal microprocessor to interface with computer. The MP160 System used for data acquisition, analysis, storage, and retrieval. MP160 system interface with AcqKnowledge 5.0 software to display signal recorded.

VMG sensor (TSD250A) used in this research. The TSD250A VMG Transducer is a sensitive accelerometer (32.64 mm diameter) for use with BIOPAC Vibromyography Systems. TSD250A used for measuring signal from targeted muscle groups such as forearm and leg muscles. It used in advanced signal analysis algorithms to monitor the small muscle vibrations that occur when a muscle activated or contracted and optimized for assessing voluntary muscle effort.

2.2. MMG signal recording

Subject evaluation was conducted on 8 healthy male volunteered subjects. The MMG signals were recorded on the dominant hand of the subject in order to reduce variability on the motor unit firing rate due to the hand domination [28]. In order to make sure that the MMG signal recorded during data collection, criteria's for volunteered subject selection have been made. Those who selected for being subjects for this research must have good physical condition with no previous or ongoing history of neuromuscular or musculoskeletal disorder specific to the elbow, wrist and/or finger joints. These criteria's will determine result of research for the cross-talk signal collected.

2.3. Muscle contraction protocol

Subject requires to seat at ease on a chair with forearm adjusted comfortably using arm support attached to the chair. Subject is requires to execute five muscle contraction with three trials of each hand exercise gesture using egg-shaped exercise ball. There are 5 minutes of rest between each set of contraction and trials before execute to next hand exercise gesture as shown in Figure 1. The hand exercise gestures according to the list below:

a. Grip strength supinated (5 times in 25s, rest 120s)
b. Flexion fingers (5 times in 25s, rest 120s)
c. Pinch grip (5 times in 25s, rest 120s)

(a) (b) (c)

Figure 1. Exercise gestures, (a) Grip streng supinated, (b) Finger flexion, (c) Pinch grip

2.4. Forearm muscle and sensor attachment

Figure 2 shows details view of the VMG sensor locations over the Palmaris Longus (PL), Flexor Carpi Ulnaris (FCU), Extensor Digitorum (ED) and Extensor Carpi Ulnaris (ECU) muscles. The position of each muscle studied determined according to the anatomical guide for the electromyographer by Perotto and Delagi [29] as follows:

a. PL-Located at the flexor side, the PL muscle determined start in the middle of the palm and straight back
b. FCU-Located at the flexor side, two fingerbreadths from the pinky border on one third of the distance between the medial epicondyle of humerus and distal head of ulna
c. ED-Located at the extensor side, one third of the distance from proximal end of a line from lateral epicondyle of humerus to distal head of ulna
d. ECU-Located at the extensor side, just lateral to ulnar border on the half way of the distance between the lateral epicondyle of humerus and distal head of ulna

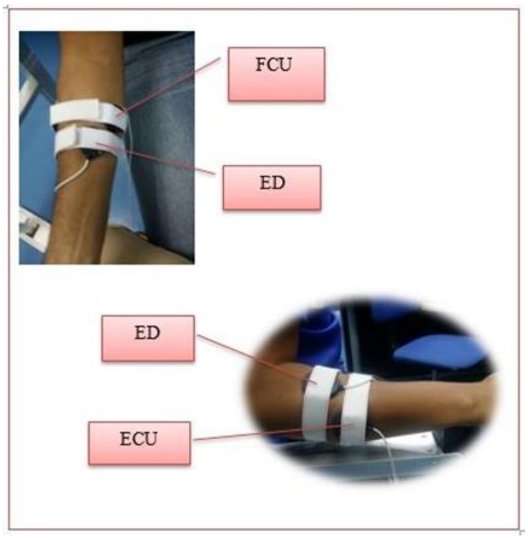

Figure 2. Sensor placement on forearm muscles

2.5. MMG signal processing

The VMG sensor and software algorithm is advance technology provided by BIOPAC System to optimize assessing voluntary muscle effort. VMG sensors located over the muscle belly to record the signal or small vibrations of activated muscle.The sensor was made completely with band-pass filter that can eliminate artifacts motion. In addition, the software used also automated with VMG analysis to simplify the process and generate filtering signal that correlate with the contraction muscle studied. The VMG calculation channels display a flat line during data collection and automatically perform the VMG filter calculation and analysis when the recording stops.

In this study, five contraction muscle were extracted per participant. This study included 3 trials of 3 hand gesture exercise (GSS, FF and PG) for 4 muscles (PL, FCU, ED and ECU) that resulted in 36 (3×3×4) number of samples or features per participant. Since 8 volunteers participated in this study, thus the feature vector size extracted were=288 (8 participants×3 trials×3 hand gesture×4 muscles).

2.6. Feature extraction

There are four types of feature extraction used in this study which Mean Absolute Value (MAV), Standard Deviation (STD), Variance (VAR) and Root Mean Square (RMS). Root Mean Square (RMS) is the value of the continuous voltage that results the same power disposal as the time averaged power disposal of the voltage. The definition is similar for the RMS value of the current. Variance defined as calculated by taking the differences between each number in the set and the mean, squaring the differences and dividing the sum of squares by the number of values in the set. All these time domain features extracted from the filtered MMG signal so that it can be classify during classification method accordingly. The equation of feature extraction used in this research shown below:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

$$STD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x_{i+i} - x_i)^2} \quad (2)$$

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}x_i^2 \quad (3)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \quad (4)$$

where: N=Total number of data
i=Length of MMG signal
x_i=MMG signal in a segment

2.7. Classification

The goal of classifier is to utilize the decision function (parameters got with the training data and sample labels) to classify the new data. The quality of a classifier can be evaluated by criterions such as classification error, computational complexity, robustness, et al. In this research, Linear Discriminant Analysis (LDA) is chose due to its functionality and computational efficiency, used as a method used in pattern recognition and machine learning. Classification accuracy for pattern recognition will generate using Minitab 18.

3. RESULTS AND ANALYSIS

The MMG signals recorded from eight subjects using MP160 BIOPAC System VMG integrated with VMG sensor (TSD250A) that includes band-pass filtering to eliminate most motion artifacts including physiologic tremor. The signal recorded for 30 seconds for five contraction muscles. The sampling rate of the signal is set to 1 kHz. Thus, each muscle channel consist approximately 30000 sample data per 30 seconds. Figure 3 shows the sample of raw and filtered signal recorded in this research.

Four features assigned to extract the recorded signal, which are MAV, STD, VAR and RMS. Therefore, recorded signal from 8 subjects were extracted for the classification process in order to determine the percentage accuracy. Table 1 to Table 3 show the sample of extracted features for different hand motion.

Linear Discriminant Analysis (LDA) used as a type of classifier to determine the accuracy. Table 4 shows the summary of classification for MAV generated with Minitab 18.1 version. The average classification accuracy across all participant and all test session for MAV, STD, VAR and RMS are 87.5%, 66.70%, 58.30% and 70.8%. Table 5 shows the summary of accuracy for all feature extraction used in this research. It can be conclude that, MAV is a suitable type of feature extraction to feed the LDA classifier to determine accuracy compared to other features because it gives high percentage accuracy.

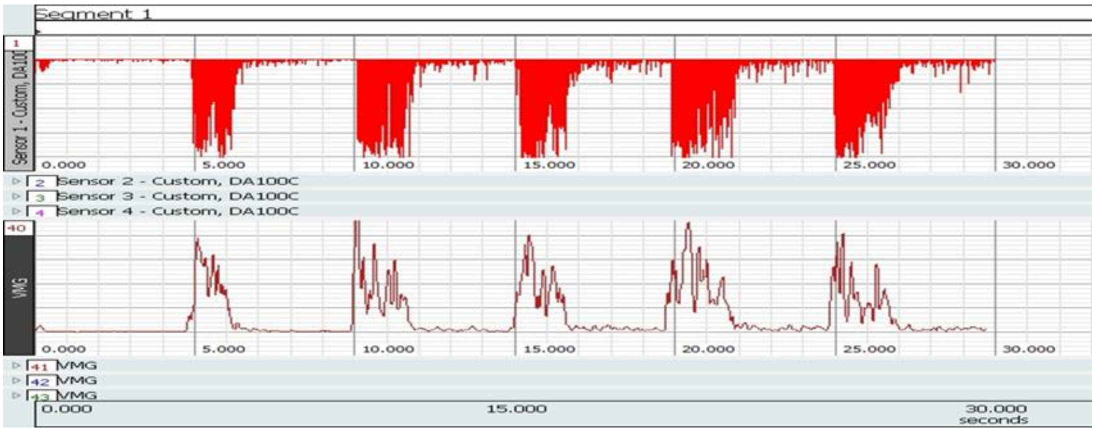

Figure 3. Raw and filtered signal

Table 1. The Value of MAV for grip strength supinated

No of subject	PL	FCU	ED	ECU
1	4.474204	7.192291	6.367886	5.093908
2	4.237892	6.654973	6.669146	3.853415
3	4.297067	7.294806	7.229205	4.37714
4	5.314596	7.451518	6.724006	5.458795
5	5.389766	8.022732	8.260413	7.104242
6	5.609553	6.576809	6.369818	5.015977
7	7.880922	11.65724	8.544292	8.882246
8	7.253859	11.28344	7.159505	7.842413

Table 2. The value of MAV for finger flexion

No of subject	PL	FCU	ED	ECU
1	7.584724	12.25349	8.54998	7.635234
2	5.664509	8.264346	7.232361	1.644206
3	6.58752	10.17895	13.19895	2.990501
4	6.034186	7.132029	7.233987	2.115165
5	5.449422	8.875302	10.4099	5.734949
6	4.873937	6.567246	8.464613	3.728056
7	8.301196	12.01424	11.82964	9.586717
8	7.432737	13.31492	12.59372	8.52413

Table 3. The value of MAV for pinch grip

No of subject	PL	FCU	ED	ECU
1	5.866773	9.681647	7.337535	5.799286
2	3.637239	5.511408	4.231339	2.583357
3	4.998462	7.91393	7.691287	4.002384
4	3.283647	6.754001	3.557011	2.503242
5	3.046358	6.324395	7.264932	4.235655
6	4.555272	7.891798	3.319327	3.691704
7	5.85815	9.705409	7.479138	6.297772
8	4.653041	8.821394	5.075026	5.020524

The average classification accuracy show that the dissimilarity and repeatability of MMG signal which is enough to allow recognition of multiple muscle activation states with highest accuracies. Moreover, the finding result support the previous research [30] where researchers discloses that MMG signal is effective in classifying more than two hand-motion patterns even with only one channel signal.

In terms of classification accuracy, the result proves the previous research [27] when the researchers conclude that that two-channel of MMG signal is enough to identify and classify the hand-motion patterns recognition. In this research, there are four channels MMG signal placed into adjacent muscles which PL-FCU and ED-ECU. Most of subjects gives similar range of MMG signal for the adjacent muscle for feature extraction values. In addition, the number of accuracy might affected by the nature of the forearm muscle structures itself due to adjacent muscle reacted each other.

Table 4. Summary of classification using LDA for MAV

Put into Group	FF	GSS	PG
FF	7	0	0
GSS	1	7	1
PG	0	1	7
Total N	8	8	8
N correct	7	7	7
Proportion	0.875	0.875	0.875

Table 5. Summary of accuracy for all feature extraction

Classification	MAV	STD	VAR	RMS
LDA	87.50%	66.70%	58.30%	70.8%

4. CONCLUSION

In this research, a study that monitor muscle activities for the purpose of hand gesture recognition is completed. MAV is the selected feature from the MMG signal to feed to the LDA classifier because it gives highest classification accuracy, which is 87.50% compared to other features. For further research, more study focus on MMG signals can be explore in any other fields especially medical field, where it can use for clinical diagnostic tool to identify neuromuscular diseases and rehabilitation process. Besides that, the MMG signal can be recorded with different force for every hand motion. Thus, the result might be used for rehabilitation study in determine recovery period and suitable exercise which focus on forearm muscles.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the support from the Fundamental Research Grant Scheme (FRGS) under a grant number of FRGS/1/2015/TK04/UNIMAP/02/5 from the Ministry of Higher Education Malaysia.

REFERENCES

[1] Y. Hong-liu, Z. Sheng-nan, and H. Jia-hua, “MMG Signal and Its Applications in Prosthesis Control,” in *International Convention on Rehabilitation Engineering & Assistive Technology*, 2010, pp. 4.

[2] J. Silva, W. Heim, and T. Chau, “A self-contained, mechanomyography-driven externally powered prosthesis,” *Arch. Phys. Med. Rehabil.*, vol. 86, no. 10, pp. 2066–2070, 2005.

[3] M. T. Tarata, “Mechanomyography versus electromyography, in monitoring the muscular fatigue.,” *Biomed. Eng. Online*, vol. 2, p. 3, Feb. 2003.

[4] G. Trager, G. Michaud, S. Deschamps, and T. M. Hemmerling, “Comparison of phonomyography, kinemyography and mechanomyography for neuromuscular monitoring,” *Can. J. Anesth.*, vol. 53, no. 2, pp. 130–135, 2006.

[5] T. W. Beck, T. J. Housh, G. O. Johnson, J. T. Cramer, J. P. Weir, J. W. Coburn, and M. H. Malek, “Does the frequency content of the surface mechanomyographic signal reflect motor unit firing rates? A brief review,” *J. Electromyogr. Kinesiol.*, vol. 17, no. 1, pp. 1–13, 2007.

[6] J. Silva, W. Heim and T. Chau, "MMG-based classification of muscle activity for prosthesis control," *The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Francisco, CA, 2004, pp. 968-971.

[7] J. T. Cramer, T. J. Housh, J. P. Weir, G. O. Johnson, J. M. Berning, S. R. Perry, and A. J. Bull, “Gender, muscle, and velocity comparisons of mechanomyographic and electromyographic responses during isokinetic muscle actions,” *Scand. J. Med. Sci. Sport.*, vol. 14, no. 2, pp. 116–127, 2004.

[8] C. Murphy, N. Campbell, B. Caulfield, T. Ward, and C. Deegan, “Micro Electro Mechanical Systems Based Sensor For Mechanomyography,” *Biosignal*, 2008.

[9] H.-B. Xie, Y.-P. Zheng, and J.-Y. Guo, “Classification of the mechanomyogram signal using a wavelet packet transform and singular value decomposition for multifunction prosthesis control.,” *Physiol. Meas.*, vol. 30, no. 5, pp. 441–457, 2009.
[10] S. Narayanan, M. R. M. Irfan, B. Geethanjali, and S. P. Kumar, “MMG as a Communication Channel for the Disabled,” *IOSR J. Eng.*, vol. 2, no. 6, pp. 1429–1432, 2012.
[11] M. O. lusola Ibitoye, N. A. zah Hamzaid, J. M. Zuniga, N. Hasnan, and A. K. hairi A. Wahab, “Mechanomyographic parameter extraction methods: an appraisal for clinical applications,” *Sensors (Basel).*, vol. 14, no. 12, pp. 22940–22970, 2014.
[12] M. Tarata, A. Spaepen, and R. Puers, “The accelerometer MMG measurement approach, in monitoring the muscular fatigue,” *Meas. Sci Rev*, vol. 1, no. 1, pp. 47–50, 2001.
[13] N. Alves, E. Sejdic, B. Sahota, and T. Chau, “The effect of accelerometer location on the classification of single-site forearm mechanomyograms,” *Biomed. Eng. Online*, vol. 9, no. 1, p. 23, 2010.
[14] T. Uchiyama and Y. Miyazaki, “Independent component analysis of mechanomyogram detected with an acceleration sensor in motion,” in *IFMBE Proceedings*, 2013, vol. 39 IFMBE, pp. 461–464.
[15] E. D. Ryan, T. W. Beck, T. J. Herda, M. J. Hartman, J. R. Stout, T. J. Housh, and J. T. Cramer, “Mechanomyographic amplitude and mean power frequency responses during isometric ramp vs. step muscle actions,” *J. Neurosci. Methods*, vol. 168, no. 2, pp. 293–305, 2008.
[16] A. O. Posatskiy and T. Chau, “The effects of motion artifact on mechanomyography: A comparative study of microphones and accelerometers,” *J. Electromyogr. Kinesiol.*, vol. 22, no. 2, pp. 320–324, 2012.
[17] M. Watakabe, K. Mita, K. Akataki, and Y. Itoh, “Mechanical behaviour of condenser microphone in mechanomyography,” *Med. Biol. Eng. Comput.*, vol. 39, no. 2, pp. 195–201, 2001.
[18] S. Kawakami, N. Kodama, N. Maeda, S. Sakamoto, K. Oki, Y. Yanagi, J. I. Asaumi, T. Maeda, and S. Minagi, “Mechanomyographic activity in the human lateral pterygoid muscle during mandibular movement,” *J. Neurosci. Methods*, vol. 203, no. 1, pp. 157–162, 2012.
[19] N. Alves, T. H. Falk, and T. Chau, “A novel integrated mechanomyogram-vocalization access solution,” *Med. Eng. Phys.*, vol. 32, no. 8, pp. 940–944, 2010.
[20] T. W. Beck, T. J. Housh, G. O. Johnson, J. P. Weir, J. T. Cramer, J. W. Coburn, and M. H. Malek, “Comparison of a piezoelectric contact sensor and an accelerometer for examining mechanomyographic amplitude and mean power frequency versus torque relationships during isokinetic and isometric muscle actions of the biceps brachii,”, *Journal of Electromyography and Kinesiology.* vol. 16, pp. 324–335, 2006.
[21] L. Qi, J. M. Wakeling, A. Green, K. Lambrecht, and M. Ferguson-Pell, “Spectral properties of electromyographic and mechanomyographic signals during isometric ramp and step contractions in biceps brachii,” *J. Electromyogr. Kinesiol.*, vol. 21, no. 1, pp. 128–135, 2011.
[22] P. Kaczmarek, J. Celichowski, H. Drzymała-Celichowska, and A. Kasiński, “The image of motor units architecture in the mechanomyographic signal during the single motor unit contraction: in vivo and simulation study,” *J. Electromyogr. Kinesiol.*, vol. 19, no. 4, pp. 553–563, 2009.
[23] T. W. Beck, M. a Dillon, J. M. DeFreitas, and M. S. Stock, “Cross-correlation analysis of mechanomyographic signals detected in two axes.,” *Physiol. Meas.*, vol. 30, no. 12, pp. 1465–1471, 2009.
[24] N. Alves and T. Chau, “Uncovering patterns of forearm muscle activity using multi-channel mechanomyography,” *J. Electromyogr. Kinesiol.*, vol. 20, no. 5, pp. 777–786, 2010.
[25] N. Alves, T. Chau, and A. D. Collection, “Classification of the mechanomyogram : its potential as a multifunction access pathway,” pp. 2951–2954, 2009.
[26] J. Silva and T. Chau, “Coupled microphone-accelerometer sensor pair for dynamic noise reduction in MMG signal recording,” *Electron. Lett.*, vol. 39, no. 21, p. 1496, 2003.
[27] N. Alves and T. Chau, "Recognition of forearm muscle activity by continuous classification of multi-site mechanomyogram signals," *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, Buenos Aires, 2010, pp. 3531-3534.
[28] A. Adam, C. J. De Luca, Z. Erim, J. L. Dideriksen, F. Negro, R. M. Enoka, D. Farina, P. Contessa, and C. J. D. E. Luca, “Hand Dominance and Motor Unit Firing Behavior Hand Dominance and Motor Unit Firing Behavior,” *Journal of Neurophysiology.* pp. 1373–1382, 2014.
[29] E. F. Perotto, A., & Delagi, “Anatomical Guide for the Electromyographer: The Limbs and Trunk: Charles C Thomas.,” 2005.
[30] Y. Zeng, Z. Yang, W. Cao, and C. Xia, “Hand-motion patterns recognition based on mechanomyographic signal analysis,” *FBIE 2009-2009 Int. Conf. Futur. Biomed. Inf. Eng.*, pp. 21–24, 2009.

BIOGRAPHIES OF AUTHORS

Mohamad Razif Mohamad Ismail received his Diploma and B.Eng degree in mechatronic engineering from Universiti Malaysia Perlis, Perlis, Malaysia in 2013 and 2016, respectively. He is currently pursue PhD study with Fast Track Program at Universiti Malaysia Perlis. Registered on Board Engineer Malaysia (BEM) 2017. His main area of research interests includes biomedical instrumentation and physiological signal processing on human muscles activity specficically in mechanomyography and electromyography signals.

Lam Chee Kiang received his B.Eng. and Ph.D. degree in mechatronic engineering from Universiti Malaysia Perlis, Perlis, Malaysia, in 2009 and 2014, respectively. He is currently a Senior Lecturer in the School of Mechatronic Engineering, Universiti Malaysia Perlis and registered as a Professional Technologist with MBOT (Ts.). His main area of research interests includes image processing, signal processing on human muscles activity, and virtual reality surgical simulator.

Kenneth Sundaraj is Professor in Faculty of Electronics and Computer Engineering, UTeM. He is registered as a Professional Engineer with BEM (Ir.), ECUK (CEng.), FEANI (EurIng.) and senior member of IEM (MY), IET (UK) & IEEE (US). He is additionally registered as an International Professional Engineer (IntPE), Asia-Pacific Economic Cooperation Engineer (APEC Engineer) and with the Association of Southeast Asian Nations (ASEAN Eng). His current research interests are biomedical instrumentation, physiological signal processing and kinesiology. He has also published in the areas of virtual reality, image processing and vision systems.

Mohd Hafiz Fazalul Rahiman received B.Eng. (Hons.) degree in electrical control and instrumentation, and the M.Eng. and Ph.D. degree in electrical engineering from Universiti Teknologi Malaysia (UTM), Johor, Malaysia, in 2003, 2005, and 2013, respectively. In 2006, he joined Universiti Malaysia Perlis (UniMAP), Malaysia, as a Teaching Staff Member and currently holds an Associate Professor position. His research interests include Ultrasonics; Tomography Imaging; Sensor and Instrumentation; Internet-of-Things (IoT) and Embedded System.